A Novel Non-local Means based Technique for Simultaneous Denoising and Fusion

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ABSTRACT

Image fusion and denoising have been widely researched as separate techniques for the past few decades. Most of the fusion techniques fuse the images with the assumption that images are non-noisy. But in many practical applications, especially, in the case of satellite images this assumption fails. In this paper, a novel technique based on nonlocal means filter in conjunction with multiresolution contourlet transform for simultaneous image denoising and fusion is proposed. Recently developed shrinkage technique is used at the detail coefficients for the purpose of denoising. A change in the multiresolution framework is proposed by applying a nonlocal means filter at the approximate coefficients that further reduces the effect of noise. The process of image fusion is carried out in the multiresolution framework by applying suitable fusion rule. Advantages of simultaneous denoising and fusion technique has been demonstrated qualitatively and quantitatively with a wide number of quality metrics.

Keywords:

nonlocal means, contourlet transform, fusion, shrinkage

1. INTRODUCTION

There has been a growing interest in the field of image fusion for the last few decades. Applications of fusion can be found in various fields including medical, remote sensing and military. The most popular fusion techniques are based on image pyramids and wavelets which have been proposed in the literature quite oftenly. The need for fusion arises due to the fact that under different lightning conditions, especially in poor light conditions, in visible spectrum, though images are taken with sophisticated imaging sensors, fail to show the targets. A solution to this problem would be to fuse two or more images coming from different sensors having redundant information to produce a single fused image which preserves all relevant information from the original data. Thus fusion is a technique of combining multiple sources of data into a single composite image such that the fused image contains all important information from all sources. Apart from medical, and remote sensing applications, other fusion applications include classification [25], target identification [11] and object detection [27]. In [3, 13] authors have developed appropriate fusion techniques to extract salient information from given number of images while fusing. Comparison between multiresolution (MR) techniques for fusion of images for various applications have been proposed in [24, 20, 19]. Additionally, these MR techniques have also proven to be an effective tools for image denoising as well. Few other applications of MR denoising include, edge detection [6], image enhancement [15] and improved classification [4].

Many image fusion methods stated above assume the images to be non-noisy while fusing. But it is observed in many practical situations that the images may be perturbed with some kinds of noises. Noise gets introduced due to poor lightning conditions while capturing medical images, satellite images like multispectral and hyperspectral and other types of images. To remove the noise from the image, some methods preprocess the images before fusion and quite a few postprocess. But, it is observed that in either case, efficiency of the fusion process degrades. In this paper, a simulataneous denoising and fusion has been carried out; thus providing higher efficacy. Further both denoising and fusion process have been carried in the multiresolution framework where, image is decomposed into detail and approximate coefficients at various levels.

In multiresolution denoising technique, an appropriate threshold to the MR transform coefficients is applied that suppress the effect of noise while preserving the edges and detail informations. Two such popular and widely used methods for thresholding are hard and soft thresholding. In hard thresholding technique, all the coefficients below the set threshold are rejected and reduced to zero. On the contrary, in soft thresholding such coefficients are reduced to zero by the magnitude of the threshold. Two popular techniques which make use of either soft and hard thresholding are discrete wavelet transform (DWT) [14], dual-tree complex wavelet transform (DT-CWT) [10] and contourlet transform (CT) [16].

In this paper multiresolution technique (MRT) technique has been employed to decompose the image into approximate and detail subbands at various scales. There have been a wide variety of strategies proposed in literature for effective denoising. The widely used methods include VisuShrink [12], SureShrink [8], BayesShrink [21] and NeighShrink [9]. In the proposed method soft thresholding has been applied at detail coefficients and nonlocal means filter [1] which is a popular non-linear filter is employed to the approximate coefficients for edge preserved denoising.

Although mutiresolution technique such as discrete wavelet transform has good frequency and spatial localization property, by which it is possible to handle vertical and horizontal edges efficiently, edges oriented along arbitrary directions are not handled properly while denoising. To overcome this difficulty, contourlet transform has been used as a multiresolution technique to decompose noisy image instead of wavelet transform. The performance of the proposed algorithm has been tested with a wide number of

quality metrics such as peak signal to noise ratio (PSNR), universal quality index (UQI) [28], fusion factor (FF) [18] and edge factor (EF) [26]. Peak signal-to-noise ratio (PSNR) is not the reliable quality metric with respect to human visual system (HVS). SSIM is an objective quality measure based on the structural content of the image. Hence structural similarity index measure (SSIM)[29] is additionally adopted as the quality metric.
The paper is organised as follows. In Section 2 the literature on fusion based methods has been reviewed. A brief introduction of nonlocal means and contourlet transform is given in Section 3. The framework for simultaneous denoising and fusion of image is also discussed in the same Section. The experimental results of the proposed method for assessment of fusion and denoising using noisy test images are discussed in Section 4. Final conclusions are given in Section 5.

2. LITERATURE ON IMAGE FUSION

Multiresolution analysis methods such as, wavelet, contourlet and pyramid techniques have been widely discussed in literature. But there are also papers in which fusion techniques based on color related methods such as, IHS transform; Statistical/numerical methods such as, weighted combination, Brovey, PCA, HPF etc.,have been discussed. Each techniques posess some advantages and disadvantages over the others. Techniques based on weighted combination degrade the contrast of source images. With IHS transform spectral distortion is observed. PCA techniques have their own drawbacks since these techniques rely on the strong correlation between the image data being replaced and the replacing data. Fusion techniques those work on spatial domain combine the pixel values of the two or more images to be fused in a linear or nonlinear way. Final fused image is obtained by a weighted average of the registered input images. For example, let $I_1, I_2, ..., I_N$, be the registered input images, and let $a_1, a_2, ..., a_N$ be the weights then the fused image F becomes,

$$F = a_1(I_1) + a_2(I_2) + ... + a_N(I_N) \tag{1}$$

where $a_1+a_2+...+a_N = 1$. Another category of fusion algorithms are based on pyramid transforms, such as, Laplacian or Gaussian pyramids. Multi-resolution image pyramids are constructed by filtering the image successively and then downsampling. In these types of fusion techniques, initially, registered images are subjected to pyramid transform and then fused using any rule. The fused image is obtained by performing the inverse transformation. These methods fail to provide good fused results when the images are noisy as noise tends to have higher contrast and this will be selected over cleaner images. Wavelet transforms have been successfully used in many fusion schemes in recent years. Many fusion techniques have been proposed using discrete wavelet ransform (DWT) [5, 13] as these have proved to be better compared to pyramid techniques due to less blocking artefacts, better directional information and improved perceptual quality. But there are certain drawbacks of DWT worth to be mentioned. A shift variant nature is observed in DWT while sub-sampling at each level due to which a small shift in the input causes a completely different distribution of enery between DWT coefficients at different scales [10].
It is also observed that the fields like pattern recognition, visual enhancement, object detection and surveillance also make use of the concept of integrating the data to obtain more information from different sensors. In [17], the authors have provided in-depth information on multiple sensor data. In this paper, the authors have explained the concepts and methodology of image fusion for multisensor integration oriented data processing. There are quite a large number of papers which talk on improving fusion quality and applications related to remote sensing area. Simone et al. [22] obtained elevation maps for synthetic aperture radar (SAR) interferometers and the fusion of multi sensor and multi temporal SAR images. Quite a few papers have been published recently [7, 23, 2] that provide history, developments, and the current state of the art of image fusion methods.

3. SIMULTANEOUS DENOISING AND FUSION

In the proposed method, contourlet transform has been used as a MRT technique as this transform offers a much richer set of directions and shapes, and thus, this transform is more effective in capturing smooth contours and geometric structure in the image.

3.1 Contourlet Transform

Contourlet transform [16] is an extension of the cartesian wavelet transform in two dimensions using multiscale and directional filter banks. In contourlet transform, it is possible to expand the image using basis images oriented at various directions in multiple scales, with flexible aspect ratio; thus, possesing the properties like multi-scale, time frequency localization and degree of directionality. Contourlets are capable of capturing geometric smoothness of the contour along any possible directions without using separable basis functions. This transform has been implemented in two stages; the subband decomposition stage and the directional decomposition stage.
For subband decomposition stage, Laplacian pyramid is used. Laplacian pyramid decomposition generates a sampled lowpass version of the two images. One being the original image and the other is a difference between the original and the prediction image. The directional filter bank (DFB) is implemented by using a t-level binary tree decomposition that leads to 2^t subbands with wedge shaped frequency partitioning as shown in Fig.1 (a). Here subands 0-3 correspond to horizontal directions and 4-7 correspond to vertical directions. A t-level tree structured DFB is equivalent to 2^t parallel channel filter bank with equivalent filters and overall sampling matrice as illustrated in Fig.1 (b). From figure, it is observed that a combination of anlysis H_k and synthesis G_k filters form the complete DFB. Here k value ranges between $0 \leq k < 2^t$. The sampling matrices forms the diagonal form given by

$$f_k = \begin{cases} \text{diag } (2^{t-1}, 2), & \text{for } 0 \leq k < 2^{t-1} \\ \text{diag } (2, 2^{t-1}), & \text{for } 2^{t-1} \leq k < 2^t. \end{cases} \tag{2}$$

The two sets correspond to the horizontal and vertical set of directions, respectively. Thus, the combination of Laplacian pyramid and directional filter banks yield the discrete contourlet transform. The important point to be noted in the contourlet transform is that the two decomposition stages i.e., multiscale and directional decomposition are independent to each other which further facilitate to decompose each scale into different number of directions. Fig.2 illustrates subband formation with contourlet domain. For the subbands I-VIII, soft thresholding technique has been applied, further details are provided in subsequent sections. For the subband 0 that represent low frequency components present in the image, a nonlocal means filter is applied.

3.2 Nonlocal Means Filter

The observation model for a noisy image u is written as

$$u = v + \eta \tag{3}$$

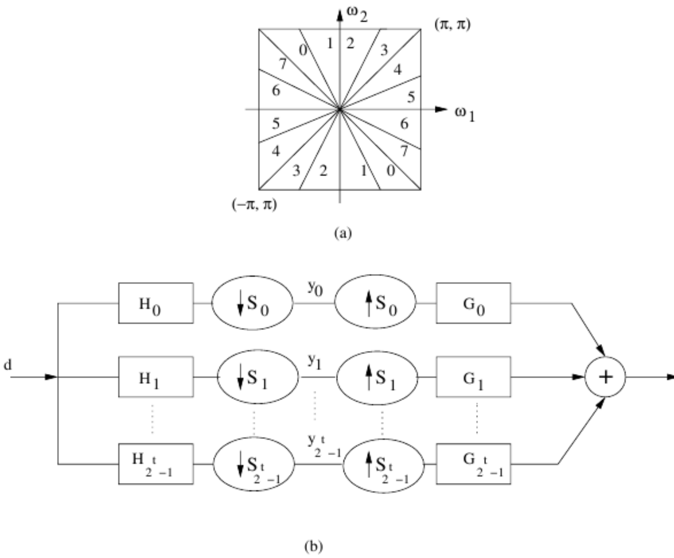

Fig. 1. Illustration of directional decomposition stage. (a) Frequency patitioning with directional filter bank with t=3. (b) t-level tree structure of the directional filter bank.

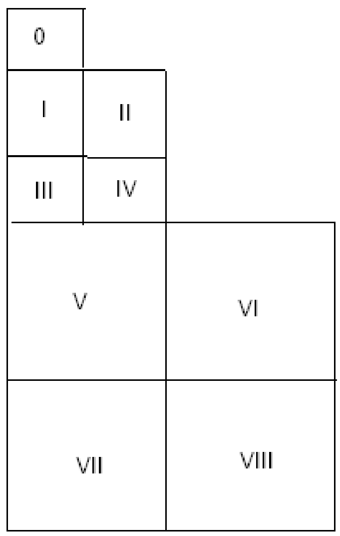

Fig. 2. Illustration of subband formation with a contourlet transform.

where v is the original image and η is a zero mean additive random noise with standard deviation σ. In NLM strategy each noisy pixel is replaced by an weighted average of all the pixels in the image.

$$\hat{v}(i) = \sum_j w(i,j)u(j) \quad (4)$$

where weight $w(i,j)$ is computed by comparing neighbourhood of pixel i under consideration with all other neighbourhoods around pixel j for a given patch size.

$$w(i,j) = \frac{1}{Z(i)} \exp\left(\frac{-\left\|u(\mathcal{N}^p(i)) - u(\mathcal{N}^p(j))\right\|_2^2}{h^2}\right) \quad (5)$$

here $\mathcal{N}^p(i)$ and $\mathcal{N}^p(j)$ represent the square patches of size $(2p+1) \times (2p+1)$ centered at i and j, respectively and p is half length of the patch. Z is a normalization term $Z(i) = \sum_j w(i,j)$ and h decides the extent of filtering and hence refered as the filtering parameter.

3.3 Methodology

The framework for simultaneous denoising and fusion is as illustrated in Fig.3. As stated before, images of multisensor devices to be fused could be noisy. It is therefore important to suppress the noise prior to fusion. Here images corrupted with i.i.d random noise have been considered which are further decomposed using contourlet and DWT transform to obtain MR coefficients. MR coefficients are denoised using soft thresholding and then suitable fusion rule is applied to combine denoised coefficients. Final fused image is obtained by applying inverse MR transform MRT^{-1} operation. The noisy image is decomposed by contourlet transform. A proposed change in this technique is to apply a nonlocal means filter to the approximate coefficients as illustrated in Fig.4. Soft thresholding is applied to the subbands I-VIII shown in Fig.2 that correspond to the higher frequency components. Thus, additional noise is removed and edges can be preserved by applying nonlocal means filter to the subband-0. The contourlet decomposition of the noisy signal is obtained by

$$K = W^l n \quad (6)$$

K are the contourlet transform coefficients. W^l is an l-stage contourlet transform and n is the signal to be analysed. For thresholding of the transform coefficients soft thresholding is implemented as

$$\hat{F}_i = \begin{cases} sgn(K_i)(|K_i - Thr), & |K_i| \geq Thr \\ 0, & |K_i| < Thr. \end{cases} \quad (7)$$

where Thr is the threshold. The inverse wavelet transform of the thresholded coefficients can be written as,

$$\hat{f} = (W^l)^{-1}\hat{F} \quad (8)$$

where f is the denoised estimate of the noisy signal n, $(W^l)^{-1}$ is the inverse contourlet transform. For fusion of MR coefficients we implement three fusion rules:
a) Maximum selection (MS).
b) Weighted average (WA).
c) Window based verification (WBV).
Contourlet coefficients that represent high frequancy components or coefficients in the detail subbands (I-VIII) have large absolute values compared to the coefficients in the subband-0. Hence these coefficients represent the salient features in the image such as lines, edges and region boundaries. The image details, edges, and small structural features are important which have to be preserved in the fusion process. We select fusion strategy which while fusing preserves important features. As image details, edges and structural features are represented by local contrast changes, so a fusion rule that select the maximum of the absolute value is selected. This approach is known as the maximum selection (MS) rule. A weighted average (WA) scheme also known as match and selection rule proposed by Burt et al. [3] uses an activity measure and the similarity between each coefficient as the criteria for fusion. It is observed that this selection process ensures that all important information is retained while artefacts due to opposite contrast are reduced. A correlation matrix measures the similarity between the corresponding transform coefficients. Final fused image is obtained by a weighted

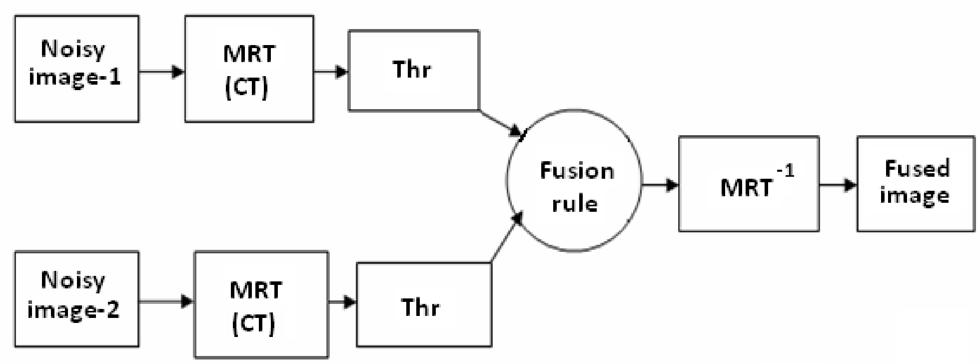

Fig. 3. Illustration of the framework for simultaneous denoising and fusion.

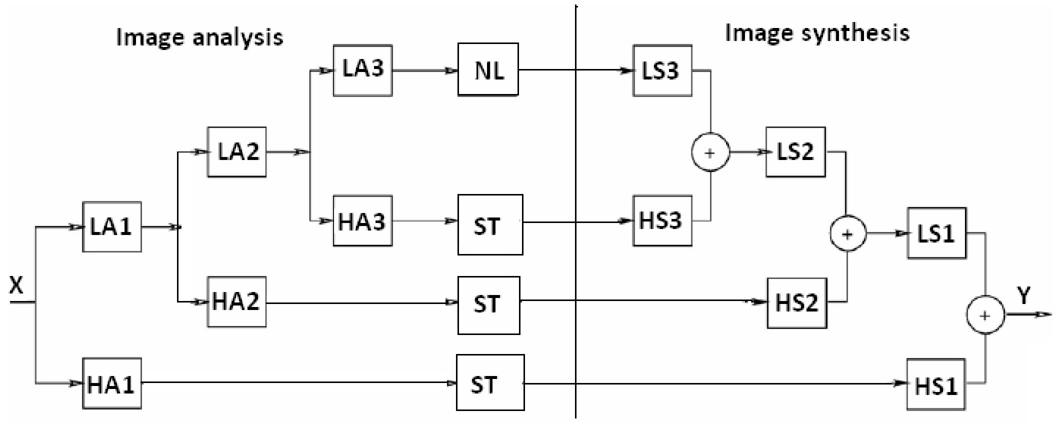

Fig. 4. Illustration of the proposed change in the multiresolution technique (MRT). Here the term NL and ST denote nonlocal means filter and soft thresholding, respectively.

averaging scheme where, the weights are based on match and selection measures. In both above mentioned fusion rules, averaging is performed on corresponding approximate coefficients (coefficients related to the low frequency region) of the transform. A consistency checking method proposed by Li et al. [14] is a window based verification (WBV) scheme. This method is based on the binary decision mapping in which decision of the selection process is based on a local activity indicator. Selected window size ranges between the values 3×3 to 5×5.

4. EXPERIMENTAL RESULTS

We have carried out the experimentation on different types of images and reported results for the well known images clock and pepsi, simulated with i.i.d. random noise. A set of experimentation is also carried on multispectral image data. A multispectral image is the one that captures image data at specific frequencies across the electromagnetic spectrum. Quality metrics such as PSNR, Entropy and Std. deviation have been used to validate experimental results for clock and pepsi images whereas, SSIM, UQI, FF and EF are used as quality metrics along with PSNR to validate results for multispectral image as these quality metrics play a important role in the validation of satellite images. Fig.5 and Fig.6 show the results for clock and pepsi images. Fig.5(a),(b) and Fig.6(a),(b) show input images of clock and pepsi simulated with i.i.d random noise with $\sigma = 10$ and $\sigma = 20$, respectively. Fig.5 (c) and Fig.6 (c) show the results for these images for three level wavelet decomposition with Daubechies' biorthogonal DWT (DB2.2) which produces three directional detail subband images, LH, HL, HH representing the horizontal, vertical, and diagonal directions, and an approximation image LL. For the approximation band LL nonlocal means filter is applied. Soft thresholding is applied to all detail subbands. Fusing the images is carried out with weighted averaging (WA) fusion rule which is found to be providing good results compared to other fusion rules. Though this method is able to fuse the images quite well, the resultant image is noisy which can be observed from the corresponding figure. Fig.5 (d) and Fig.6 (d) show the results obtained with contourlet transform for three level decomposition. These results are better compared to the previous results. The reason being the fact that the contourlet transform performs better than the wavelet transform in both denoising and in fusion applications, a fact which has been already proved. But close observation of these results reveal that there appear some artefacts in these images. Fig.5 (e) and Fig.6 (e) show the results for the proposed method where, both input images have been decomposed with a single level contourlet transform and then soft thresholding has been applied to all detail subbands and approximate subbands are processed with

Table 1. Comparative results for clock image.

MR Technique	Noise variance	PSNR (dB)	Entropy	Std.dev.
DWT (3 level)	10	28.08	6.71	39.73
Contourlet(3 level)		30.08	6.91	39.91
Proposed: (Contourlet+NL)		32.58	7.13	**40.23**
DWT (3 level)	15	27.39	6.53	38.51
Contourlet (3 level)		29.79	6.73	38.73
Proposed: (Contourlet+NL)		31.15	6.95	**39.13**
DWT (3 level)	20	26.88	6.39	38.13
Contourlet (3 level)		29.08	6.61	38.23
Proposed: (Contourlet+NL)		30.58	6.81	**38.51**

Table 2. Comparative results for pepsi image.

MR Technique	Noise variance	PSNR (dB)	Entropy	Std.dev.
DWT (3 level)	10	28.19	6.65	39.56
Contourlet (3 level)		29.38	6.89	39.71
Proposed (Contourlet+NL)		31.43	7.01	**39.93**
DWT (3 level)	15	27.95	6.43	38.37
Contourlet (3 level)		28.99	6.64	38.53
Proposed (Contourlet+NL)		30.85	6.87	**38.79**
DWT (3 level)	20	27.38	6.49	37.23
Contourlet (3 level)		28.58	6.52	37.55
Proposed: (Contourlet+NL)		29.88	6.73	**37.71**

a nonlocal means filter. From the result it is observed that the proposed method provides better fused results compared to all the techniques mentioned before. In addition, it removes the noise very well while retaining the sharpness present in the image. Table.1 and Table.2 provide comparative results for the images clock and pepsi respectively. From the tables it is observed that the proposed method provides better results compared to stand-alone wavelet and contourlet based MR techniques with three levels of image decomposition. The proposed method provides better results with respect to PSNR, Entropy and Std.deviation quality metrics.

Visual comparison for multispectral data fusion along with denoising is given in Fig.7. Top row shows the multispectral images in different bands simulated with $\sigma = 20$. It is observed that few bands correspond to smooth variations present in the image and a few correspond to high frequency components. Hence these images have to be fused to obtain composite image that posesses both low and high frequency components. It is observed that the technique of DWT (3 level) shown in Fig.7 (c) leaves behind some noise whereas, the result corresponding to Fig.7(d) that is based on contourlet transform has some artefact effect. However, with the proposed method images have been better fused and result is quite sharp. In addition, it removes the noise very well which can be observed from Fig.7 (e). Table.3 provides comparative results obtained for multispectal data. Here comparative results are given for all three fusion rules mentioned in the previous section. From the table it is observed that the proposed method outperforms all other methods with respect to all the quality metrics. The PSNR, SSIM, UQI and EF values are higher for the proposed method than the other methods. It is also observed that the weighted average (WA) fusion rule provides best results compared to other fusion rules.

Table 3. Comparative results for multispetral data for $\sigma = 20$.

MR Technique	Fusion rule	PSNR (dB)	SSIM (%)	UQI	EF
DWT (3 level)	Max	23.75	56.21	0.35	0.15
	WA	24.41	59.22	0.37	0.13
	WBV	24.08	57.99	0.36	0.14
Contourlet (3 level)	Max	24.53	62.95	0.36	0.16
	WA	25.81	67.00	0.38	0.17
	WBV	25.32	65.48	0.37	0.15
Proposed: (Contourlet+NL)	Max	25.31	65.51	0.43	0.18
	WA	**26.34**	**69.82**	**0.45**	**0.19**
	WBV	25.84	67.99	0.44	0.17

5. CONCLUSIONS

In this paper, a novel technique of simultaneous denoising and fusion is proposed. Most of the fusion based methods fail to provide better results when the images to be fused contain noises. In this paper, a algorithm which removes the noise effectively while fusing is proposed using contourlet transform, which has proven to be better than wavelet transform in both denoising and fusion applications. Detail coefficients are processed with soft-thresholding for noise removal while, approximate coefficients are subjected to a nonlocal means filter to remove the additional noise. Images have been fused corresponding to their subbands with fusion rules. The efficacy of the proposed method has been tested with a wide number of quality metrics.

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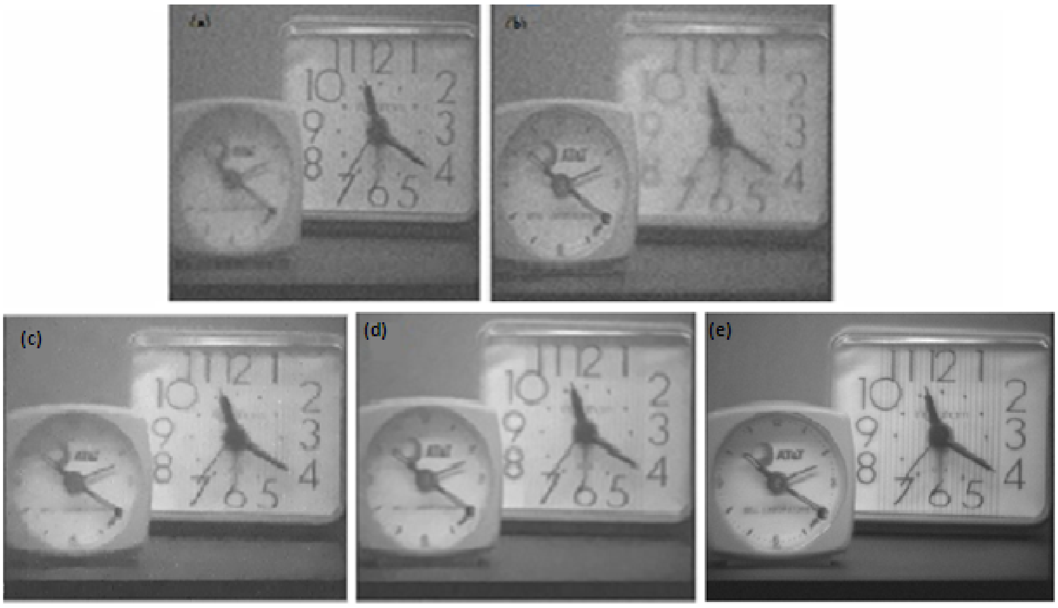

Fig. 5. Comparisons among different mutiresolution techniques. (a), (b) original clock images simulated with $\sigma = 10$, denoised results obtained with (c) DWT (3-level), (d) Contourlet (3-level) and (e) the proposed method.

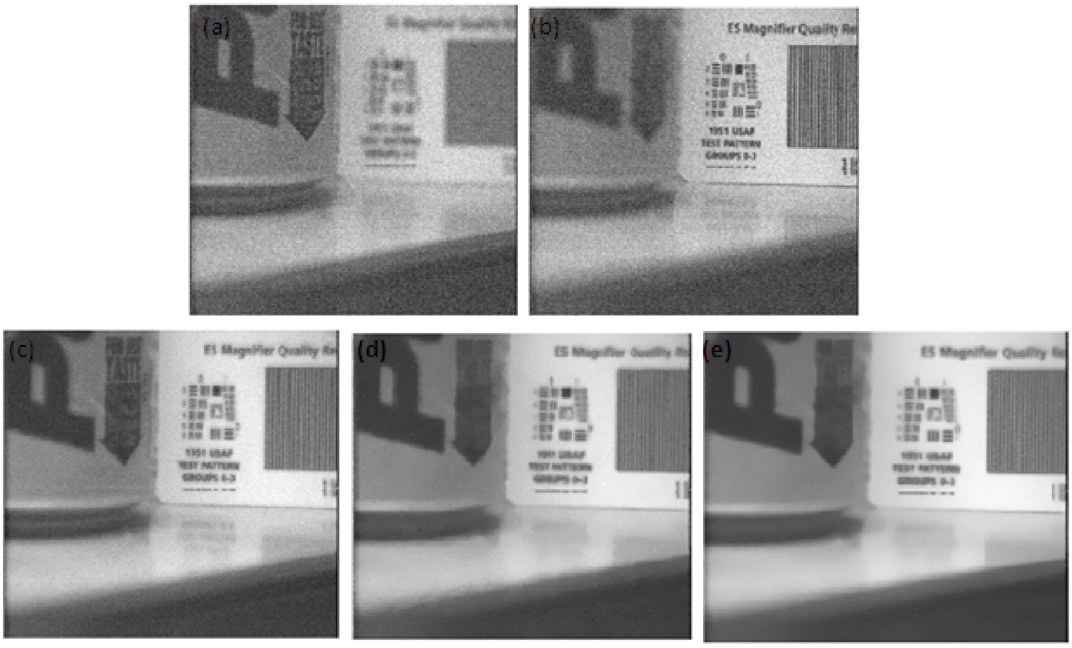

Fig. 6. Comparisons among different mutiresolution techniques. (a), (b) original pepsi images simulated with $\sigma = 20$, denoised results obtained with (c) DWT (3-level), (d) Contourlet (3-level) and (e) the proposed method.

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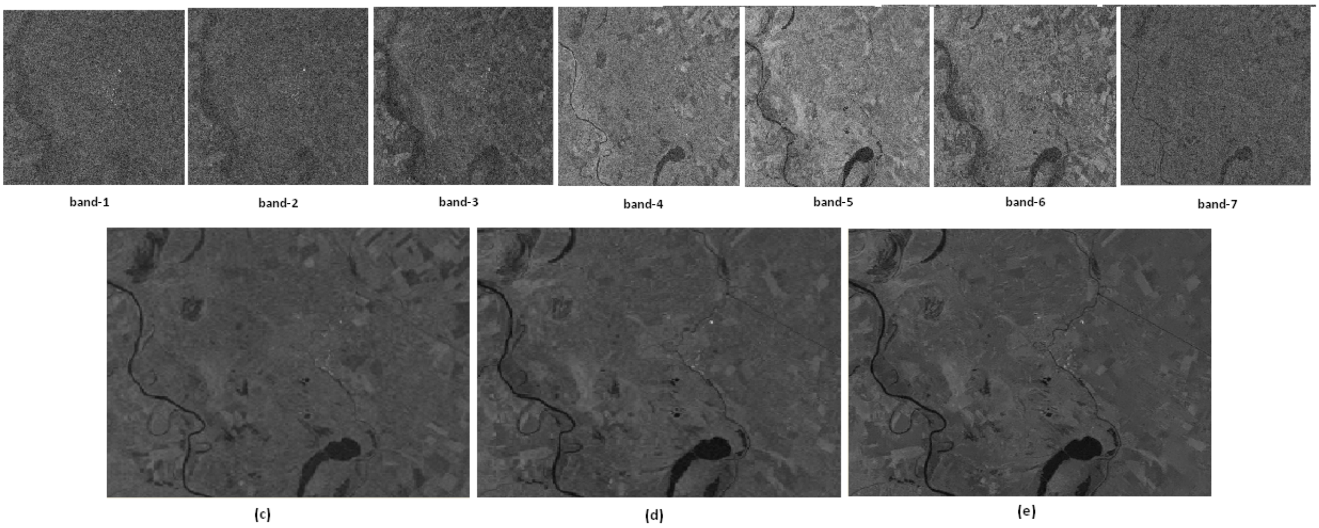

Fig. 7. Comparisons among different mutiresolution techniques. (Top row) : multispectral images in different frequency bands simulated with $\sigma = 20$, (bottom row) : denoised results obtained with (c) DWT (3-level), (d) Contourlet (3-level) and (e) the proposed method.

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