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Performance Comparision of Different Image Fusion Techniques for Multi-Focus and Multi-Modal Images

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Abstract: ***Image fusion is the process of combining information from two or more images of a scene into a single composite image that is more informative and is more suitable for visual perception or computer processing. The objective in image fusion is to reduce uncertainty and minimize redundancy in the output while maximizing relevant information particular to an application or task. Given the same set of input images, different fused images may be created depending on the specific application and what is considered relevant information. In this paper, we compare different image fusion techniques such as DWT, DTCWT and Curvelet Transform by using different types of filters and decomposition levels for multi-focus images and multi-modal images.***

Keywords: Image fusion, Curvelet Transform, multi-focus, multi-modal.

1. Introduction

Often a single sensor cannot produce a complete representation of a scene. Visible images provide spectral and spatial details, and if a target has the same color and spatial characteristics as its background, it cannot be distinguished from the background. If visible images are fused with thermal images, a target that is warmer or colder than its background can be easily identified, even when its color and spatial details are similar to those of its background. Fused images can provide information that sometimes cannot be observed in the individual input images. Successful image fusion significantly reduces the amount of data to be viewed or processed without significantly reducing the amount of relevant information[1]. In this paper, we concern the fusion of multi-view/multi-focus and multimodal images.

Since last few decades, an extensive number of approaches to fuse visual image information. These techniques vary in their complexity, robustness and sophistication. Remote sensing is perhaps one of the leading image fusion applications with a large number of dedicated publications.

The PCA image fusion method [2] basically uses the pixel values of all source images at each pixel location, adds a weight factor to each pixel value, and takes an average of the weighted pixel values to produce the result for the fused image at the same pixel location. The optimal weighted factors are determined by the PCA technique. The PCA image fusion method reduces the redundancy of the image data.

Super-resolution (SR) reconstruction[3] is a branch of image fusion for bandwidth extrapolation beyond the limits of a traditional electronic image system. Katartzis and Petrou describe the main principles of SR reconstruction and provide an overview of the most representative methodologies in the domain. The general strategy that characterizes super-resolution comprises three major processing steps which are low resolution image acquisition, image registration/motion compensation, and high resolution image reconstruction. Katartzis and Petrou presented a promising new approach based on Normalized Convolution and a robust Bayesian estimation, and perform quantitative and qualitative comparisons using real video sequences.

Mitianoudis and Stathaki demonstrate the efficiency of a transform constructed using Independent Component Analysis (ICA) and Topographic Independent Component Analysis based for image fusion in this study [4]. The bases are trained offline using images of similar context to the observed scene. The images are fused in the transform domain using novel pixel-based or region-based rules. An unsupervised adaption ICA-based fusion scheme is also introduced. The proposed schemes feature improved performance when compared to approaches based on the wavelet transform and a slightly increased computational complexity. The authors introduced the use of ICA and topographical ICA based for image fusion applications. These bases seem to construct very efficient tools, which can complement common techniques used in image fusion, such as the Dual-Tree Wavelet Transform. The proposed method can outperform the wavelet approaches. The Topographical ICA based method offers a more accurate directional selectivity, thus capturing the salient features of the image more accurately.

Li and Yang first described the principle of region-based image fusion in the spatial domain [5]. Then two region-based fusion methods are introduced. They proposed a spatial domain region-based fusion method using fixed-size blocks. Experimental results from the proposed methods are encouraging. More specifically, in spite of the crudeness of the segmentation methods used, the results obtained from the proposed fusion processes, which consider specific feature information regarding the source images, are excellent in terms of visual perception. The presented algorithm, spatial domain region-based fusion method using fixed-size blocks, is computationally simple and can be applied in real time. It is also valuable in practical applications.

2. Image Fusion Techniques

In this section, we will discuss about different image fusion techniques such as Discrete Wavelet Transform(DWT), Dual-Tree Complex Wavelet Transform(DTCWT) and Curvelet Transform for multi-view and multi-modal images.

2.1 DWT Based Image Fusion

Wavelet transform is a mathematical tool developed originally in the field of signal processing. It can also be applied to fuse image data following the concept of the multi-resolution analysis (MRA). The multi-resolution wavelet transform is an intermediate representation between Fourier and spatial representations[2]. It can provide good localization properties in both spatial and Fourier domains. 2-D Discrete Wavelet Transformation (DWT) converts the image from the spatial domain to frequency domain. In DWT, two channel filter bank is used. By applying the 1-D discrete wavelet transform (DWT) along the rows of the image first, and then along the columns to produce 2-D decomposition of image, the wavelet transform decomposes the image into low-low, low-high, high-low and high-high frequency components as shown in figure.

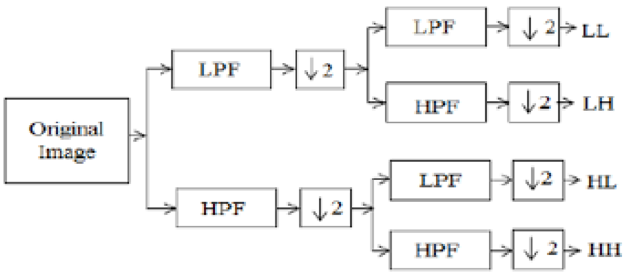


Figure 1: DWT Decomposition

These four components are referred to as approximation, horizontal, vertical and diagonal coefficients respectively because low-low frequency components contains average information whereas the other components contain directional information due to spatial resolution. Higher absolute values of wavelet coefficients in the high bands correspond to salient features such as edges or lines. In DWT based image fusion(figure-2), first DWT is applied to source images to obtain wavelet coefficients and appropriate fusion rule is used. Finally, Inverse DWT is applied for reconstruction of final fused image.

2.2 DT-CWT Based Image Fusion

DWT techniques have number of disadvantages such as they need number of convolution calculations, require more memory resources and takes much time, which hinder its applications for resource constrained battery powered visual sensor nodes[6]. DCT based fusion methods need less energy as compare to the DWT techniques. the basic

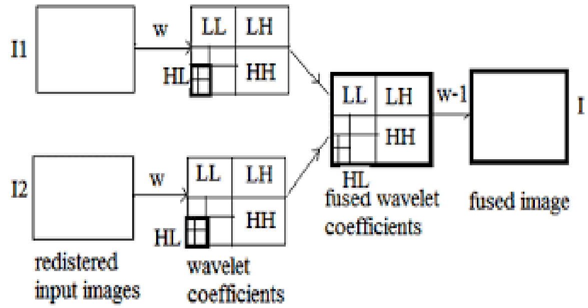


Figure 2: DWT Fusion

The DT-CWT employs two real Discrete Wavelet Transform by splitting the real and imaginary parts of transform into two trees[7]. The technique uses delayed samples between the real part and its correspondence imaginary part in each level in combination with the alternate odd length and even length linear phase filters.

By considering a 2D wavelet $\psi(x, y) = \psi(x)\psi(y)$ associated with row-column implementation of wavelet transform, where $\psi(x)$ is a complex wavelet given by

$$\psi(x) = \psi h(x) + j\psi g(x),$$

the expression for $\psi(x, y)$ obtained is given as

$$\psi(x, y) = [\psi h(x) + j\psi g(x)]\ [\psi h(y) + j\psi g(y)]$$
$$= \psi h(x)\psi h(y) - \psi g(x)\psi g(y) + j[\psi g(x)\psi h(y) + \psi h(x)\ \psi g(y)]$$

$$\text{Real Part}\{\psi(x,y)\} = \psi h(x)\psi h(y) - \psi g(x)\ \psi g(y) \quad (1)$$

$$\text{Imaginary Part}\{\psi(x,y)\} = \psi g(x)\psi h(y) + \psi h(x)\ \psi g(y) \quad (2)$$

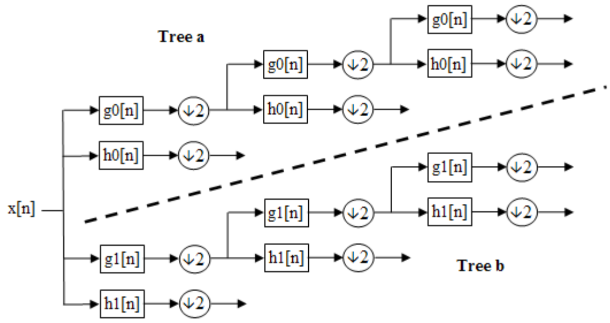


Figure 3: Practical Implementation of DTCWT

The real part of this complex wavelet is obtained as the difference of two separable wavelets and is oriented in -450. Real 2D wavelet oriented at +450 can be obtained by making $\psi(x, y) = \psi(x)\ \psi(y)^*$, where $\psi(y)^*$ is the complex conjugate of $\psi(y)$. Four more oriented real wavelets in the direction of +750 ,- 750 +150 and -150 can be obtained by repeating the above procedure on $\Phi(x)\psi(y)$, $\Phi(x)\psi(y)^*$, $\psi(x)\Phi(y)$, $\psi(x)\Phi(y)^*$. The real part of the complex Dual Tree wavelet Transform alone constitutes the Real Oriented 2D Dual Tree Transform. The spectrum of Imaginary part of complex 2D wavelet in 2D frequency plane is same as its real part oriented at -450. This transform give rise to six distinct directions and there are two wavelets in each direction as shown in Figure1. One of the wavelet can be interpreted as the real part of a complex valued 2D wavelet and the other wavelet is interpreted as the imaginary part of a complex 2D wavelet. The magnitude of each complex wavelet is an approximately circular bell-shaped function. Real version of Dual tree transform is two times expansive whereas the complex version of Dual Tree transform is four times expansive.

2.3 Curvelet Based Image Fusion

While dealing with the curve, wavelet transform becomes inefficient as it is linear function and decompose image in a isotropic manner. In this type of decomposition, more wavelet coefficients and more levels of decompositions are needed. Moreover, it requires large amount of time to get fully decomposed image[7][8]. Curvelets and ridgelets take the form of basic elements, which exhibit very high directional sensitivity and are highly anisotropic. Therefore, the curvelet transform represents edges better than wavelets, and is well-suited for multi-scale edge enhancement[9]. Curvelet functions are characterized by scale, orientation and translational parameters, values of which are adaptably defined. The curvelet transform has four stages:[7]

2.3.1 Sub-Band Decomposition

In this step, the image is divided into individual sub-band frequencies. Mathematically, it is given by:

$$f\ \alpha\ (P0f,\ \Delta 1f, \Delta 2f,\ K) \qquad (3)$$

where ‘f’ is image matrix or function, ‘P0’is low pass filter, Δ1,Δ2,................ are band pass filters.

2.3.2 Smooth partitioning

A grid of dyadic squares is defined:

$$Q_{(s,k_1,k_2)} = \left[\frac{k_1}{2^s}, \frac{k_1+1}{2^s}\right] \times \left[\frac{k_2}{2^s}, \frac{k_2+1}{2^s}\right] \in \mathbf{Q}_s \qquad (4)$$

Qs – all the dyadic squares of the grid. Let w be a smooth windowing function with ‘main’ support of size $2^{-s} \times 2^{-s}$. For each square, ‘w_Q’ is a displacement of w localized near Q. Multiplying $\Delta_s f$ with w_Q (∀Q∈Qs) produces a smooth dissection of the function into ‘squares’. The windowing function w is a nonnegative smooth function.

2.3.3 Renormalization

Renormalization is centering each dyadic square to the unit square [0,1]×[0,1]. For each Q, the operator T_Q is defined as:

$$(T_Q f)(x_1,x_2)=2^s f(2^s x_1-k_1,\ 2^s x_2-k_2) \qquad (5)$$

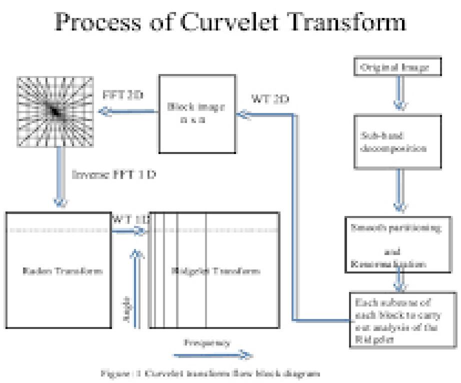


Figure 4: Curvelet Based Image Fusion Method

2.3.4 The Ridgelet Transform

Ridgelets are an orthonormal set $\{\rho_\lambda\}$ for $L^2(\Re^2)$ which divides the frequency domain to dyadic coronae |ξ|∈[2s , 2s+1]. In the angular direction, samples the s-th corona at least 2s times.[11]

3. Experimental Results and Discussion

For multi-view/multi-foucs and multi-modal images, image fusion is carried out by using DCT, DTCWT and Curvelet Transforms using different filters and different decomposition levels.

3.1 Performance Metrics

For validation of the results statistical parameters are taken into account. Four performance metrics are calculated for the original, and fused images, viz. PSNR, RMSE, cross correlation and Entropy[13][14]. The performance metrics are detailed below:

3.1.1 Peak signal to noise ratio (PSNR)

Peak signal to noise ratio is defined as ‘ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of it’s representation’.

$$PSNR=20\log_{10}[(m)/RMSE] \qquad (6)$$

where, m is the maximum value of a pixel possible. FOr, grayscale images m=255.

3.1.2 Entropy

It is defined as the amount of information present in the image. The Entropy can show the average information included in the image and reflect the detail information of the fused image. the greater the Entropy of the fused image is, the more abundant information included in it, and the greater the quality of the fusion is. According to the information theory of Shannon, The Entropy of image is:

$$E = -\sum_{i=0}^{255} \{P_i \log_2 P_i\} \qquad (7)$$

Where E is the Entropy of image, and Pi is the probability of i in the image.

3.1.3 Correlation Coefficient

Correlation Coefficient measures the correlation between the original and the fused images. The higher the correlation between the fused and the original images, the better the estimation of the spectral values The ideal value of correlation coefficient is 1.

$$r = \frac{N\Sigma XY - (\Sigma X)(\Sigma Y)}{\sqrt{[N\Sigma X^2 - (\Sigma X)^2][N\Sigma Y^2 - (\Sigma Y)^2]}} \qquad (8)$$

3.1.4 Mutual Information(MI)

Mutual information is an information theory measure of the statistical dependence between two random variables or the amount of information that one variable contains about the other. It can be qualitatively considered as a measure of how well one image explains the other.

$$MI\ (A,B) = H\ (A) + H\ (B) - H\ (A,B) \qquad (9)$$

The above are calculated for DCT, DTCWT and Curvelet Transforms using different filters and different decomposition levels.

3.2 Quantitative Analysis

We compare different numbers of decomposition levels and filters for each multi-focus and multi-modal transform. Decomposition levels from three to six are compared for each transform for multi-focus and multi-mode images. The performance metrics compared are RMSE, PSNR, Entropy, Cross Correlation and Mutual Information. In this paper, we analysed over 10 pairs of test images as shown in figure 5.

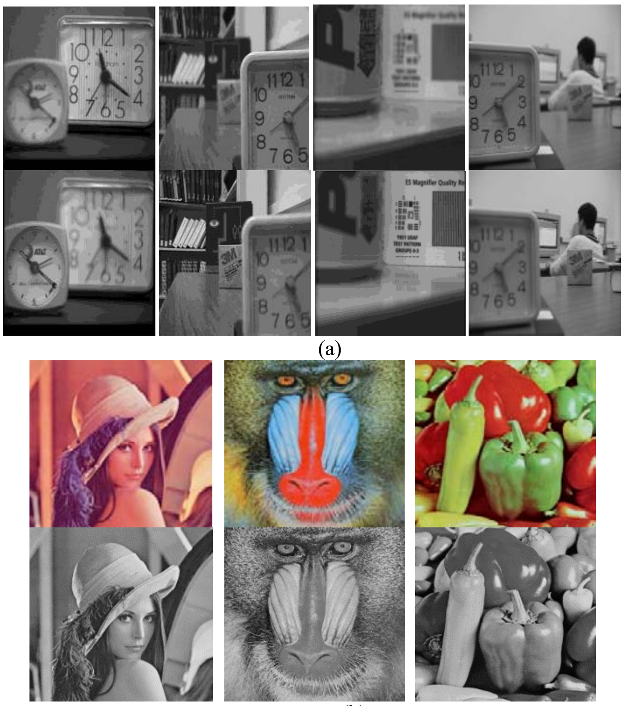


Figure 5: Test Images for (a) Multi-View Fusion (b) Multi-Modal fusion

3.2.1 DWT Fusion

For the performance comparison of DWT we used three wavelet families: Daubechies (dBN, N=1,2,3,4,5,6,10,13,15), Symlets(symNN=3,4,5,6,9,11,13)),Bioorthogonal(bior[N.N], N.N=1.3, 2.2, 3.5, 4.4, 6.2). The diffrent values of performance metrics for DWT Multi-view and multi-modal are given in table I and II respectively.

Among the results acquired by comparing different filters with different decomposition levels, the filters with best results are given in Table 1 and Table 2 for multi-view and multi-modal images respectively.

Table 1: DWT Multi-View Fusion

Filter	*level*	*Performance Metrics*			
		PSNR	*Entropy*	*CC*	*MI*
db1	4	36.1366	7.1442	0.9962	3.5727
db6	4	37.4497	7.1277	0.9972	3.6168
Sym3	5	37.9371	7.1437	0.9975	3.6956
Sym5	4	38.3348	7.124	0.9977	3.7079
Bior4.4	5	38.0655	7.1439	0.9976	3.7058

It is observed that as the decomposition level increases up to five, the performance metrics are giving better results but after further increase in decomposition levels the psnr of the fused image is increasing. Hence decomposition levels after six are not considered. It is observed that Daubechies filters show good performance compared to biorthogonal and symlet filters.

Table 2: DWT Multi-Modal Fusion

Filter	*level*	*Performance Metrics*			
		PSNR	*Entropy*	*CC*	*MI*
db1	4	25.8949	7.395	0.9873	2.9317
db6	4	28.0465	7.4045	0.9886	2.8923
Sym3	4	27.8644	7.4032	0.9883	2.9138
Sym9	4	28.212	7.4063	0.9949	2.9065
Bior4.4	5	28.077	7.4054	0.9876	2.9313

3.2.2 DT-CWT Fusion

In DT-CWT fusion, we use multiple filters depending on the levels of the transform. Here we used only two levels of filter. For first level we used Farras Nearly Symmetric Filters(FSfarras) and for second level we used Kingsbury's Q Filters (dualfilt1) for decomposition values three to six. Diffrent values of performance metrics for multi-view and multi-modal images for DTCWT fusion are given in Tables 3 and 4 respectively.

For multi-view images it is observed that as decomposition levels increases, the performance metrics increases up to level five and from level 6 the performance metrics are decreasing. Performance metrics for decomposition levels after six are not giving feasible results.

Table 3: DTCWT Multi-View Fusion

Filter	*level*	*Performance Metrics*			
		PSNR	*Entropy*	*CC*	*MI*
fsfarras and dualfilt1	3	37.7239	7.1073	0.9974	3.7088
	4	38.8907	7.1106	0.998	3.876
	5	38.9427	7.1202	0.998	3.9121
	6	38.9033	7.1309	0.9976	3.9008

For multi-mode images, it is observed that as decomposition level increases entropy and MI decreases up to level four and again increases from level 5 where as PSNR increases up to level 5 and again decreases from level 6. Hence the best results are shown at level 5.

Table 4: DTCWT Multi-Modal Fusion

Filter	level	Performance Metrics			
		PSNR	Entropy	CC	MI
fsfarras and dualfilt1	3	29.4211	7.4026	0.9886	3.1037
	4	29.7331	7.4063	0.9984	2.9915
	5	27.0137	7.4085	0.9876	2.6031
	6	26.9007	7.4037	0.9876	2.0518

3.2.3 Curvelet Fusion

In CT, the fusion is done based on Pyramid and orientaton filters. Here we use burt filters for pryamid filters and haar filters for orientaion filters are used. Different levels of decomposition filters from level three to six are used and compared and are shown in table 5 and table 6.

Table 5: Curvelet Multi-View Fusion

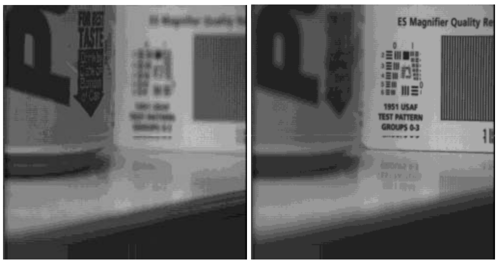
level	Performance Metrics			
	PSNR	Entropy	CC	MI
4	34.6597	7.1285	0.9956	3.7034
5	36.9767	7.1127	0.9974	3.8097
6	38.4807	7.108	0.998	3.9593
7	39.0886	7.1037	0.9982	3.9927
8	24.7763	7.3118	0.9467	1.7886

In both multi-view and multi-modal, as decomposition level increases, the performance metrics are showing better results. In multi-view curvelet fusion, the best results are obtained at level seven where as in multi-modal fusion the best results are obtained at level six.

Table 6: Curvelet Multi-Modal Fusion

level	Performance Metrics			
	PSNR	Entropy	CC	MI
3	24.9843	7.3976	0.9854	2.069
4	27.6528	7.4129	0.9852	2.9865
5	28.4968	7.4367	0.9864	3.0873
6	28.8994	7.4046	0.9862	3.0118

The results of multi-view image fusion and multi-modal fusion are given in figure 6 and figure 7 for a given test image. For both multi-view and multi-modal fusion, it is observed that curvelet fusion gives better fused image compared to DWT and DTCWT fusion.



(a)

(b) (c)

(d)

Figure 6: Multi-View Image Fusion (a) Test Images (b) DWT Fused Image (c) DTCWT Fused Image (d) Curvelet fused Image

(a)

(b) (c)

(d)

Figure 7: Multi-Modal Image Fusion (a) Test Images (b) DWT Fused Image (c) DTCWT Fused Image (d) Curvelet fused Image

4. Conclusion

From the analysis it is evident that for multi-view and multi-modal images, Curvelet fusion present good results compared to DWT and DTCWT. This is because DTCWT is shift-variant and capture more orientation than DWT. where as in CT, due to sub-sampling some important information is preserved. And also as decomposition levels increase PSNR is increasing but entropy is decreasing i.e., as decomposition levels increases noise is decreasing but information from the images are also decreasing. Hence it is observed that level five is presenting good results compared to other levels.

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