Indian Journal of Geo Marine Sciences
Vol. 46 (02), Feburary 2017, pp. 338-348

Effect of wavelet based image fusion techniques with principal component analysis (PCA) and singular value decomposition (SVD) in supervised classification

Sulochana S*, Vidhya R, Mohanraj K [1] & Vijayasekaran D

Institute of Remote Sensing (IRS), Anna University, Chennai,
1-Software Engineer, Wipro Technologies, Bangalore, Karnataka,

[*E-mail: ssulochana45@gmail.com]

Received 28 October 2014; Revised 12 November 2014

With more promotion in satellite image processing techniques and the accessibility of various resolution images, fusion is necessary to combine panchromatic and multispectral images for further applications. Recent researches show that wavelet based image fusion algorithms provide high spectral quality in the fused images, but less spatial information in fused images due to critical down sampling .To increase spatial and spectral resolution, we have implemented wavelet based image fusion algorithms along with singular value decomposition(SVD) and principal component analysis (PCA) and its influences on supervised classification. The quality of the fused images is evaluated by quantitative and qualitative measurements. Qualitative evaluation is confirmed by edge detection methods. Quantitative results proved in terms of with reference and no reference image quality metrics. Supervised classification is used to check whether the spectral distortion caused by wavelet based fusion methods and the classification accuracy is measured by Kappa index (K). Results shows wavelet based image fusion combined with Eigen value methods such as SVD and PCA improves the classification accuracy as compared to actual multispectral images. Best classification results are achieved by framelet transform with SVD based fusion.

[Keywords: Principal component analysis (PCA), Singular value decomposition (SVD), Support vector machine (SVM), discrete wavelet transform (DWT)]

Introduction

The availability of various spatial, temporal and spectral resolutions of data in different fields such as medical imaging, machine vision, remote sensing and image vision. Land use and land cover information is one of the important elements in forming policies concerning to environmental and other issues. Image fusion is necessary to integrate multisensory data for getting high resolution images.

Image fusion is a process of combining two or more images of the scene to produce better quality, high resolution images without any artefacts, such that, the fused image is more interpretable in many applications due to more accurate and better quality information. In that respect different methods have been proposed in literature such as high pass filter method [1], Brovey transform [2] and Intensity, Hue and Saturation (HIS) transform[3,4], principal component analysis(PCA)[5] .Though these spatial domain methods[6,7,8,9] gives better visual quality images, many research papers show that visual colour distortion in fused images. High pass filter method preserves spatial details, but some noises exit in the fused image. IHS transform directly replaces the intensity components by high resolution panchromatic images. However, spatial resolution improves, spectral distortion in a fused image because of replacing the intensity component .PCA method replaces the first principal component of the multispectral image by PAN images. It improves spatial quality and spectral distortion due to loss of information when reconstructing the original image.

Recently transform domain techniques have been developed that utilize the multiresolution analysis, such as wavelet transform. Wavelet transforms [10] has an ability to preserve time and frequency details. The given input images are decomposed into different levels of frequencies, and then fusion techniques are implemented by replacing the detail coefficients with detail components of another input image. Even though wavelet based image fusion provides high spectral quality, spatial resolution decreases due to critical down sampling when using remote sensing images for land use and land cover mapping.

Spatial information is essential for most of the applications owing to the complex structure of land use features. Although many image fusion methods are available in literature to integrate remote sensing data, not all the techniques meet the requirement of mapping earth surface features.

In recent time researches have used other multiresolution analyses including discrete wavelet transform (DWT)[11,12,13,14], wavelet packet transform (WPT)[15,16,17,18], atrous wavelet transform (ATWT)[19,20.21], multi wavelet transform (MWT)[22,23], curvelet transform (CUT)[24,25,26], contourlet tansform (CT)[27,28], nonsupsampled contourlet transform (NSCT)[29,30,31], and framelet transform (FRT)[32,33,34,35].

Much advancement is made in image fusion technology, but limited research has been done in further applications such as classification [36,37,38,39,40,41,42] and feature extraction [43]. Classification accuracy of remote sensing may be increased by suitable band selection and also enhancement of images such as image fusion. Training sites are selected from high resolution images but the classification accuracy is determined by the spectral quality of the images which is based on the fusion algorithm used for getting high resolution images. The objective of this paper is to review the Wavelet based image fusion, along with singular value decomposition and principal component analysis based image fusion techniques and corresponding influences in supervised classification of remote sensing images.

Image fusion using principal component analysis (PCA) and singular value decomposition (SVD)

In this paper, PCA and SVD are two Eigen value methods[44] used for image fusion. Multispectral sensor collect Land use and land cover features in adjacent bands of the electromagnetic spectrum. This causes a redundancy in the information captured by the sensor. By applying PCA the correlated bands are converted into uncorrelated new bands, the principal components, the first principal component contains a maximum variance which gives the maximum spatial information. Singular value decomposition allows eliminating the least important information to create an approximate representation with desired number of dimensions.

PCA and SVD are applied to MSS image. Then the first principal component image and first singular value component image are replaced by panchromatic (PAN) imagery whose histogram has already matched by PC1 and SVD1 image. Then the inverse PCA and SVD are performed to get a high resolution MSS image. The results are shown in (Fig.1&2).

Wavelet based image fusion with principal component analysis (PCA) and singular value decomposition (SVD)

In this paper wavelet based image fusion such as discrete wavelet transform ,wavelet packet transform , atrous wavelet transform, curvelet transform, multiwavelet transform, contourlet transform, nonsubsampled contourlet transform and framelet transform based image fusion with singular value decomposition and principal component analysis is done .

Generally discrete wavelet to transform approximation subband is split up into second level approximation and detail subbands. Wavelet packet analysis is similar to discrete Wavelet transform, the only difference is that additions to the decomposition of the approximatiom subband the wavelet detail subbands is also decomposed to approximation and detail component. Multiwavelets is an extension of scalar wavelets which uses more than two filter banks to decompose the given image. Atrous wavelet transform the given image decomposed into approximate and detail subbands which is the same dimension as the original image.

The discrete wavelet transform is shift variant due critical sub sampling. This can lead to small shifts in the input waveform causing large changes in the wavelet coefficients, large variations in the distribution of energy at different scales and possibly large changes in reconstructing waveforms. DWT is not good when isolation directional features which is not adjusted in horizontal and vertical directions.

Recently a number of approaches, which can provide sound directional features. Curvelet transform was introduced by Donoho that is another multiresolution Transform which provides more edge information which represents edges and singularities along curves is much more effectively than discrete wavelet transform which can identify only horizontal, vertical and diagonal edge image, ignoring smoothness along curves.

Contourlet transform[27] is a multiscale and directional image representation that uses a wavelet like structure for edge. Contourlet transform can perform better in representing lines, edges, contours and curves of images due to the characteristics of its directionality and anisotropy. Laplacian pyramid is used to extract point discontinuities, then directional filter banks links point discontinuities into lines. Contourlet transform also does not shift invariant due to down sampling and up sampling in both Laplacian pyramid and directional filter banks.

A modified version of contourlet transform which was made by combing a non sub sampled Laplacian pyramid and non sub sampled directional filter banks known as non sub sampled contourlet Transform[29].

More recently framelet transform has been used in many image processing applications such as super resolution and image fusion. Framelet transform is similar to wavelet transform but has some differences. Framelets has two or more high frequency filter banks, which produces more subbands in decomposition. This can achieve better time, frequency and localization ability in image processing. There is a redundancy between the framelet subbands, which means a change in coefficients of one band, can be compensated by other subbands coefficients.

After framelet decomposition, the coefficient in one subband has correlation with coefficients in the other subband. This signifies that alterations on one coefficient can be counterbalanced by its related coefficient in the reconstruction stage which produces less noise in the original image. A tight frame filter bank provides symmetry and has a redundancy that allows for approximate shift invariance. This leads to clear edges with effective denoising which is lacking in critically sampled discrete wavelet transform.

Algorithm

1. Apply PCA and SVD transformation to transform the multispectral image into the SVD and PCA components.

2. Panchromatic image is matched with PCA and SVD component image by histogram matching. So that it has the same average and variance as the first PCA and SVD component image.

3. Apply wavelet transform (DWT, WPT, AT, MWT, CUT, CT, NSCT, FRT) to decompose histogram matched PAN image and PCA and SVD component image into the wavelet coefficients respectively.

4. Replace the detail wavelet coefficients of PCA1 and SVD1 image with detail wavelet coefficient of the histogram matched PAN image.

5. Finally inverse wavelet, PCA and SVD transform is performed to get a high resolution PAN-Sharpened image. The resultant fused images are shown in (Fig.1&2).

Experimental results

In this study we have used Quickbird image with four multispectral bands with the resolution of 4m and panchromatic band with 1m resolution. Rectification is carried out through latitude and longitude from survey of India toposheet covering area Chennai-Mambalam area [13° 2'25.84"N 80°14'1.29"E] of Tamil Nadu using ArcGIS.

The work is carried out in Matlab platform. PCA and SVD are two Eigen value methods used to fuse Quickbird MSS and PAN image. PCA preserves the spatial information, but much spectral distortion due to loss of information when reconstructing original image. To improve spectral resolution SVD is used to fuse PAN and MSS images. The classification accuracy is mainly depends on the spatial and spectral quality of remote sensing images.

Many researchers[15, 45] combined PCA with wavelet transform to get high resolution images. Generally discrete wavelet transform can capture only point singularities such as edges and contours lying in vertical and horizontal directions. Missing edge information decreases the classification accuracy .Efficient edge enhancement techniques are required to extract linear features from satellite images.

We have used different type of wavelet filters, such as wavelet packet analysis, multiwavelet transform, atrous wavelet transform, curvelet transform, contourlet transform, nonsubsampled contourlet transform and framelet transform combined with SVD and PCA used for fusion.The results are shown in (Fig.1&2.)

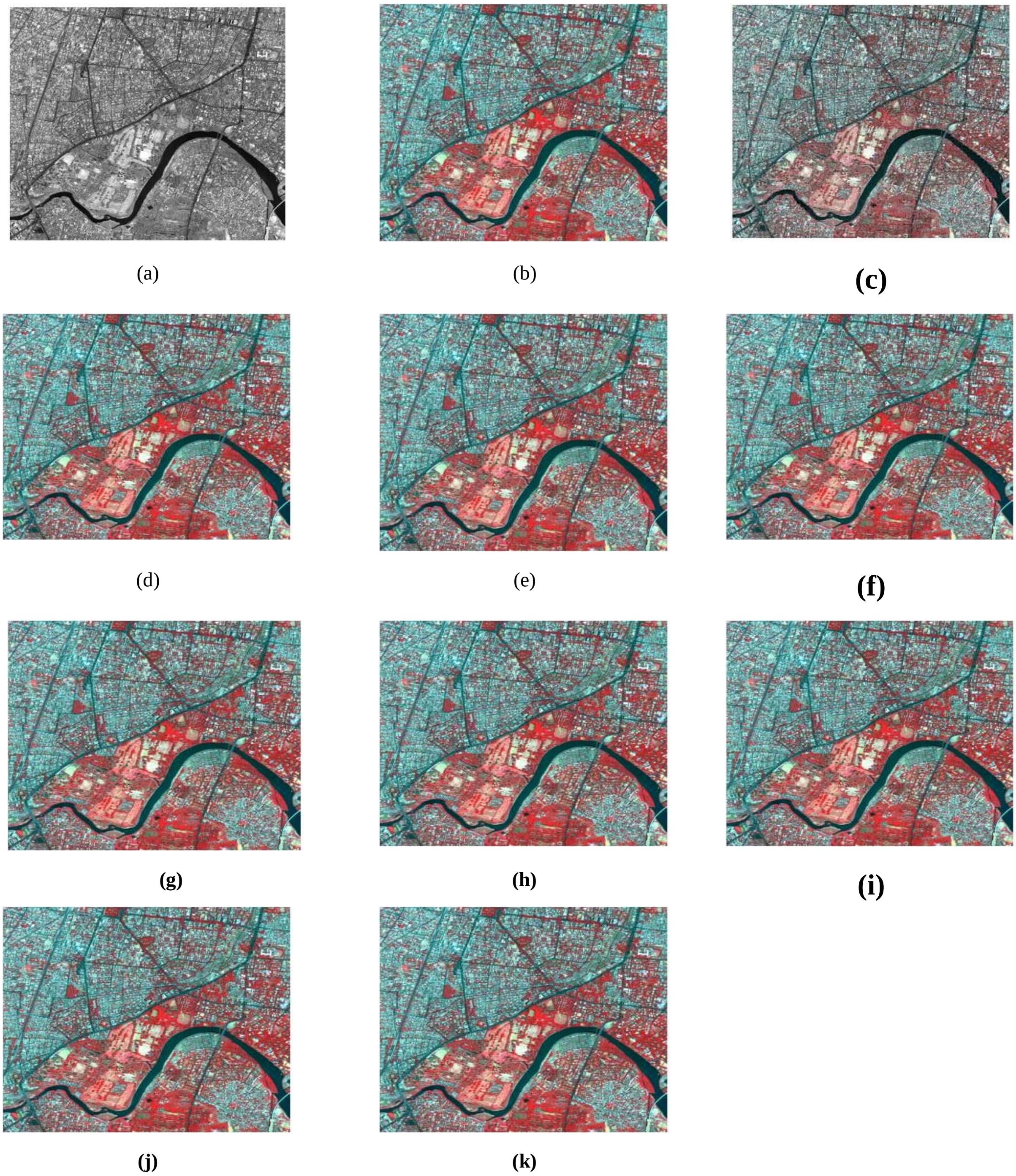

Fig.1 — Fused images with different wavelet transforms and PCA : (a) PAN image (b) Multi spectral image (c) PCA fusion (d) DWT+PCA fusion (e) WPT+PCA fusion (f) AT+PCA fusion (g) MWT+PCA fusion (h) CU+PCA fusion (i) CT+PCA fusion (j) NSCT+PCA fusion (k) FRT+PCA fusion

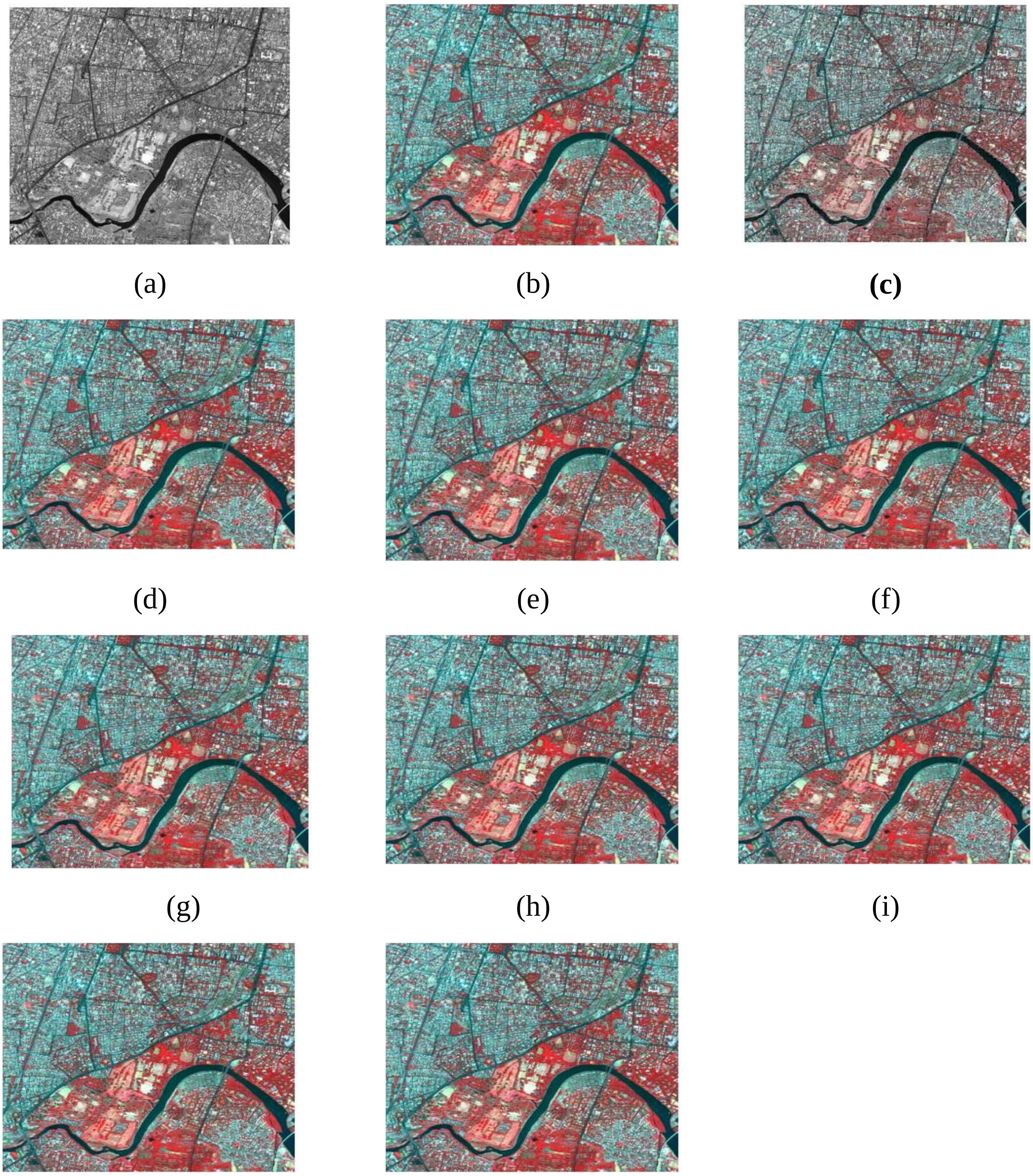

Fig. 2— Fused images with different wavelet transforms and SVD:(a).PAN image (b) Multi spectral image (c) SVD fusion (d) DWT+SVD fusion (e) WPT+SVD fusion (f) AT+ SVD fusion (g) MWT+SVD fusion (h) CU+SVD fusion (i) CT+SVD fusion (j) NSCT+SVD fusion (k) FRT+SVD fusion

Fusion evaluation criteria

The aim of image fusion is to improve the spatial and spectral information from low resolution images. So it is necessary to measure the quality of the fused images generated from different fusion methods to provide convincing results. Usually, the quality of the fused image is evaluated by using qualitative and quantitative means. Qualitative evaluation methods can be influenced by visual interpretation or manual decision and also expensive in terms of time and required equipment. So that quantitative approaches are necessary to evaluate experimental results. Many fusion metrics have been used for quantative evaluation, but there is no universally accepted metric to quantitatively evaluate the fusion results.

Qualitative evaluation with edge detection

Visual analysis is done based on Canny [46] and Edison Edge detector [47] which is used to detect edges in the Panchromatic and fused MSS bands. Overlay analysis in ArcGIS is applied to find the matching of edges in the PAN and Panchromatic and Fused MSS bands. Edges from framelet transform combined with SVD based fusion matches the high resolution actual PAN images and also concluded from Rosenfeld Edge evaluation metric [47]. This evaluation method is founded on the criteria of good edge formation without requiring for ground truth information. Continuation and thinness are two desired qualities considered when the central pixel in 3x3 widow as an edge of the detected edge map. Readers refers to the algorithm (Kitchen and Rosenfeld 1981)[48] and the results are shown in (Table 1).

Table 1— Edge evaluation using Rosenfeld evaluation metric

Fusion Method	Rosenfeld Metric		Fusion Method	Rosenfeld Metric	
	Edison	Canny		Edison	Canny
PCA	0.459	0.438	SVD	0.521	0.516
DWT+ PCA	0.472	0.456	DWT+ SVD	0.605	0.589
WPT+ PCA	0.565	0.524	WPT+ SVD	0.678	0.657
AT+ PCA	0.588	0.559	AT+ SVD	0.734	0.724
MWT+ PCA	0.620	0.589	MWT+ SVD	0.789	0.756
CUT+ PCA	0.696	0.654	CUT+ SVD	0.826	0.794
CT+ PCA	0.738	0.713	CT+ SVD	0.858	0.836
NSCT+ PCA	0.790	0.756	NSCT+ SVD	0.889	0.868
FRT+ PCA	0.826	0.810	FRT+ SVD	0.916	0.895

F ramelet transform effectively represents the edges and contours in satellite images compared to other wavelet transform. Edge features are fundamental in image processing for extracting linear features. Linear features on the earth surface have been studied and analysed by geologists for many applications such as detection of faults, ridges, joints and valleys. Enhancing edges is an effective means of enhancing spatial resolution in satellite imagery.

Quantitative evaluation

Quantitative approaches involve a set of predefined quality indicators for concluding spectral and spatial similarities between the fused image, PAN and MSS images. Image Quality assessment methods can be broadly classified into two categories: Full Reference Methods (FR) [49, 50] and No Reference Method (NR) [51, 52]. In FR, the quality of an image is measured in comparison with a reference image which is assumed to be perfect in quality. NR methods do not employ a reference image.

Metrics for fusion evaluation when reference image is available

A - The perfect image
B - The fused image to be assessed
i – Pixel row index

1. Peak Signal to Noise Ratio (PSNR)

$$PSNR = 10 \times log_{10}\left(\frac{Peak^2}{MSE}\right) \qquad (1)$$

2. Root- Mean –Square Error(RMSE)

$$RMSE = \sqrt{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(A(i,j) - B(i,j))^2} \qquad (2)$$

3. Correlation coefficient (CC)

$$Corr(A,B) = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(A(i,j)-\bar{A})(B(i,j)-\bar{B})}{\sqrt{(\sum_{i=1}^{m}\sum_{j=1}^{n}(A(i,j)-\bar{A})^2)(\sum_{i=1}^{m}\sum_{j=1}^{n}(B(i,j)-\bar{B})^2)}} \qquad (3)$$

4. Structural Similarity Index matrix (SSIM)

$$SSIM(A,B) = \frac{(2\mu_A\mu_B + C_1)(2\sigma_{AB}+C_2)}{(\mu_A^2+\mu_B^2+C_1)(\sigma_A^2+\sigma_B^2+C_2)} \qquad (4)$$

Where μ_A and μ_B are the estimated mean intensity along A,B directions and σ_A and σ_B are the standard deviation respectively. σ_{AB} can be estimated

$$\sigma_{AB} = \left(\frac{1}{N-1}\sum_{i=1}^{N}(A_i - \mu_A)(B_i - \mu_B)\right) \qquad (5)$$

C_1 and C_2 are constants and the values are given as

$C_1 = (K_1 L)^2$
$C_2 = (K_2 L)^2$
Where K_1, K_2<<1 is a small constant and L is the dynamic range of the pixel values .

5. Universal quality index (UQI)

Let $\{A_i \ |i = 1.2.3 \dots \dots \dots N\}$ and $\{B_i \ |i = 1.2.3 \dots \dots \dots N\}$ be the original and test images respectively. The Proposed quality index is defined as

$$Q = \frac{4\sigma_{AB}\bar{A}\bar{B}}{(\sigma_A^2+\sigma_B^2)\left((\bar{A}^2)+(\bar{B}^2)\right)} \quad (6)$$

Where

$$\bar{A} = \frac{1}{N}\sum_{1=1}^{N} A_i$$
$$\bar{B} = \frac{1}{N}\sum_{1=1}^{N} B_i$$
$$\sigma_A^2 = \frac{1}{N-1}\sum_{1=1}^{N}(A_i - \bar{A})^2$$
$$\sigma_B^2 = \frac{1}{N-1}\sum_{1=1}^{N}(B_i - \bar{B})^2$$
$$\sigma_{AB} = \frac{1}{N-1}\sum_{1=1}^{N}(A_i - \bar{A})\ (B_i - \bar{B})$$

The fused image which will best preserve the spectral information of the original image is the one that has the highest possible UQI.

Metrics for Fusion evaluation when Reference image is not available.

1.Entropy

$$\mathrm{H} = -\sum_{j=1}^{G} p(i)\log_2 p(d(i)) \quad (7)$$

where L denotes the number of gray level, p(i) equals the ratio between the number of pixels whose gray value and the total pixel number contained in an image.

2. Standard Deviation

$$\hat{\sigma}^2 = \frac{1}{n\times m}\sum_{j=1}^{n}\sum_{i=1}^{m}\left(x_{i,j} - \bar{x}\right)^2 \quad (8)$$

Where $\bar{x} = \frac{1}{n\times m}\sum_{j=1}^{n}\sum_{i=1}^{m} x_{i,j}$

$x_{i,j}$ is the gray level of a pixel coordinate with coordinate (i,j).

3. Spatial Frequency

$$SF = \sqrt{RF^2 + CF^2} \quad (9)$$

Where row frequency

$$RF = \sqrt{\frac{1}{m\times n}\sum_{i=1}^{m}\sum_{j=1}^{n}\left((B(i,j) - B(i,j-1)\right)^2}$$

Colum frequency

$$CF = \sqrt{\frac{1}{m\times n}\sum_{i=1}^{m}\sum_{j=1}^{n}\left((B(i,j) - B(i-1,j)\right)^2}$$

4. Quality Score

Author refers [52] and the same matlab code is downloaded from author’s website.

The quality of the fused images is evaluated with reference image and without reference image. The quality metrics results are tabulated in (Table 2&3).

The IHS and PCA methods perform well spatially while the wavelet based methods improves spectral information. Remote sensing applications, both high spatial and spectral resolution are required to achieve more accurate information extraction for classification and feature extraction. We combined Wavelet transform with PCA and SVD methods to improve spatial and spectral information.

From the fused results, we can see that wavelet based fusion improves spatial resolution and also preserve the colour of the MSS image. Standard discrete wavelet transform fails to capture linear continuity in spatial features such as edges due to critical sub sampling. Improved wavelet transform introduced to overcome this drawback. Each wavelet transform has its own directional characteristics and computation complexity. We combined eight different wavelet transforms with SVD and PCA and also calculated corresponding execution time.

The elapsed time was counted for each fusion method using Matlab(*tic)* ad *(toc*) functions. SVD combined with wavelet transform based fusion methods produce good outcomes in terms of visual, quality metrics and time complexity, compared to wavelet transform+PCA based fusion methods . Framelet based image fusion with SVD is a good approach for image fusion, reaching better outcomes than other wavelet transform with SVD based fusion methods.

Fusion Method	Quality metrics (With reference image)					Quality metrics (Without reference image)			
	PSNR	RMSE	CORR	SSIM	UQI	ENTROPY	STD	SF	Q_S
PCA	25.38	1.8123	0.6123	0.5573	0.7456	4.890	37.00	15.92	5.567
DWT+PCA	26.72	1.5202	0.6516	0.6235	0.7232	5.123	40.28	16.23	5.732
WPT+PCA	28.63	1.3215	0.6723	0.6890	0.7515	5.212	42.42	14.88	6.120
AT+PCA	30.19	1.3560	0.7200	0.7245	0.7916	5.467	48.32	18.92	6.170
MWT+PCA	31.23	0.9326	0.7915	0.7456	0.8145	5.567	49.63	21.25	6.547
CUT+PCA	31.45	1.2165	0.7462	0.7563	0.8067	6.134	49.79	25.13	6.892
CT+PCAT	32.24	0.9562	0.8015	0.7934	0.8912	6.567	50.10	28.45	7.125
NSCT+PCA	33.15	0.8735	0.8156	0.8129	0.9234	7.245	51.34	30.16	7.339
FRT+PCA	34.48	0.8226	0.8179	0.8546	0.9345	7.897	51.89	32.33	7.425

Table 3 — Quality metrics (PCA fusion)

Fusion Method	Quality metrics (With reference image)					Quality metrics (Without reference image)			
	PSNR	RMSE	CORR	SSIM	UQI	ENTROPY	STD	SF	Q_S
SVD	26.34	1.2960	0.6751	0.6457	0.7564	5.226	41.68	16.15	6.012
DWT+SVD	27.56	1.2345	0.7123	0.6934	0.8569	5.863	42.99	16.98	6.156
WPT+SVD	28.95	1.1235	0.7230	0.7230	0.9325	6.149	43.64	17.56	6.420
AT+SVD	30.56	1.0865	0.7325	0.7325	0.9389	6.832	49.70	18.65	7.325
MWT+SVD	32.45	0.9865	0.8120	0.8156	0.9456	6.896	50.16	18.92	7.479
CUT+SVD	31.78	0.9725	0.7969	0.8167	0.9444	7.099	50.98	23.66	8.265
CT+SVD	33.45	0.8250	0.8456	0.8678	0.9523	7.643	51.62	28.42	8.480
NSCT+SVD	34.16	0.7965	0.8678	0.8967	0.9643	7.832	52.80	30.22	8.932
FRT+SVD	34.98	0.7160	0.9245	0.9452	0.9756	8.105	53.94	31.35	8.975

Table 3— Quality metrics (SVD fusion)

Results and discussion

Image classification is an indispensible task in remote sensing applications. Several classification algorithms have been developed in literature from maximum likelihood classifier to advanced machine learning algorithms. Classification converts the remote sensing data into a thematic map which provides the information about the various classes such as the spatial distribution of the land use features. These maps are further used for many applications like land use planning and decision making.

In this paper, we have used ENVI supervised classification to each fusion result obtained from wavelet based fusion methods. Because this study aims to analysis whether spectral distortion caused by wavelet based fusion methods and its influences in supervised classification.

The fused images were exported into ENVI software. Supervised classification such as neural network and support vector machine with different kernel functions used. Training sites are selected using ENVI-Region of interest (ROI) tool to classify the pixel of the fused and original images as belongs to one of the two classes. The study area is covered by urban features. So that only two classes are selected to classify the fused and original images. Each classification was performed with identical training and testing pixels.

Neural network uses standard back propagation for supervised learning. Error is back propagated and the weight adjustment is made using recursive method by default setting in ENVI software package.

SVM provides a separation of class by fitting an optimal separating hyper plane to a number of training data that maximizes the separation between the classes. Training data sets are used to find optimum hyper plane and its applicability is verified by the test data sets. Selecting suitable kernel is important in the implementation and the performance of the SVM classifier.

We have used different kernel functions to classify the fused images. After classification of images, the accuracy of each classified image was evaluated using Kappa index (K) which was calculated by comparing the classified map with a manually prepared map of the building and vegetation classes. By comparing the results Radial basis function kernel produce improved classification results. The results of the classification accuracy are shown in (Table 4).

Table 4 — Results of image classification

Fusion Method	Kappa Index(K) %				Fusion Method	Kappa Index(K)%			
	Neural network classification		SVM classification			SVM classification		SVM classification	
	BU	VE	BU	VE		BU	VE	BU	VE
MSS IMAGE	65.50	66.25	66.57	67.25	MSS IMAGE	65.50	66.25	67.22	68.45
PCA	65.79	66.94	68.74	67.98	SVD	66.23	67.64	68.07	68.69
DWT+ PCA	66.70	67.43	69.10	68.44	DWT+ SVD	67.13	68.46	68.78	69.56
WPT+ PCA	67.85	68.12	69.89	68.65	WPT+ SVD	68.12	68.93	70.43	70.51
AT+ PCA	69.68	68.73	70.76	70.89	AT+ SVD	70.23	70.43	72.46	71.91
MWT+ PCA	72.65	73.62	72.55	74.68	MWT+ SVD	73.89	73.94	74.24	75.19
CUT+ PCA	70.64	72.96	71.94	73.96	CUT+ SVD	74.13	74.64	74.78	75.89
CT+ PCA	75.23	74.24	74.47	75.25	CT+ SVD	75.36	75.15	76.63	76.04
NSCT+PCA	76.49	75.46	77.32	76.45	NSCT+ SVD	76.85	76.39	78.56	77.23
FRT+PCA	77.62	76.83	77.62	77.79	FRT+ SVD	78.79	79.43	80.93	81.74

In all the cases Kappa indices (K) of the fused images using framelet transform with SVD were good compared to other fusion methods.

Conclusion

In this study, we have discussed the influences of wavelet based image fusion methods in supervised classification such as neural network and support vector machine. Singular value decomposition (SVD) and principal component analysis (PCA) based fusion methods combined with different wavelet transforms to fuse PAN and MSS images. Quantitative evaluation was done with no reference and with reference image quality metrics. Though principal component analysis based fusion method produces acceptable results, spectral distortion has loss of information when reconstructing original images. SVD based fusion gives better results, because there is no much spectral distortion and computational complexity is also less. To improve spatial and spectral quality of the fused images, SVD and PCA are combined with different wavelet transforms. Each wavelet transform has its own characteristics and complexity depends on the filter banks used. Through complexity measurements framelet based fusion combined with SVD is efficient compared to other wavelet transform, however quality metrics are almost similar. Qualitative measurements are too expensive in terms of manual work and time. Canny and Edison edge detection was employed to check the detected edge images matches with edges of PAN image and also checked randomly using ArcGIS overlay analysis. The quality of the detected edges was measured by Rosenfeld evaluation metrics which also indicates framelet based fusion produces high quality edges. Spectral distortion through fusion was measured by ENVI supervised classification such as neural network and Support vector machine. The classification accuracy was measured by the Kappa index (K).Results shows framelet with SVD based fusion; along with support vector radial basis kernel function produces sound results.

Acknowledgement

The authors wish to thank Institute of remote sensing (IRS), Anna University, Chennai for providing image samples used in this paper.

References

1 Shettigara, V.K., A generalized component substitution technique for spatial enhancement of multispectral images using a higher resolution data set, *Photogramm. Eng. Rem. Sens*, (1992), 58 (5): 561–567.

2 Civco, D.L., Wang, Y., Silander, J.A., Characterizing forest ecosystems in Connecticut by integrating Landsat TM and SPOT panchromatic data. *In: Proceedings 1995 Annual ASPRS/ACSM Convention*, Charlotte, NC. 2, (1995): 216–224.

3 Carper, W.J., Lillesand, T.M., Kiefer, R.W., The use of intensity-hue-saturation transformations for merging SPOT panchromatic and multispectral image data. *Photogramm. Eng. Rem. Sens* , 56 (4), (1990): 459–467.

4 Tu, T.M., Su, S.C., Shyu , H.C., Huang, P.S ., A new look on HIS fusion methods , *Information Fusio*n,2(3), (2001): 177-186.

5 Chavez, P.S., Kwarteng, A.Y., Extracting spectral contrast in Landsat thematic mapper image data using selective component analysis. *Photogramm. Eng. Rem. Sens*, 55 (3),(1989): 339–348,

6 Chavez, P.S., Sildes, S.C., Anderson, J.A., Comparison of three different methods to merge multiresolution and multispectral data: Landsat TM and SPOT panchromatic. *Photogramm. Eng. Rem. Sens*. 57 (3), (1991): 295–303,

7 Metwalli, M.R. Nasr, A.H., Allah, O.S.F. , El-Rabaie, S., Image fusion based on principal component analysis and high-pass filter, *International Conference on Computer Engineering & Systems* , Cairo , (1991) :63-70.

8 Gulcan Sarp., Spectral and spatial quality analysis of pan sharpening algorithm: A case study in Istanbul, *European journal of remote sensing*, (2014):19-28.

9 Wang J., Wang ,C ., Wang ,X., An experimental research on fusion algorithms of ETM+ image. *International Conference on Geoinformatics*, Beijing, 18-20 June, (2010): 1-6.

10 Soman, K.P, Resmi, N.G., Ramachandran, K.I, Insight into Wavelets: from Theory to Practice, PHI Learning Pvt. Ltd, (2010).

11 Mallat, S.G., A theory for multiresolution signal decomposition: The wavelet representation, *IEEE Trans. Pattern Analysis and Machine Intelligence*, 11(7), (1989): 674-693.

12 Li, H. , Manjunath, B.S., Mitra, S.K., Multi-sensor image fusion using the wavelet transform, *International conference on image processing*, Austin ,TX, 13-16 November , (1994):51-55 .

13 Du, Y., Vachon, P.W., Vander Sanden, J.J., Satellite image fusion with multi-scale wavelet analysis for marine applications. *Can.J. Remote Sens*. 29(1), (2003): 14–23.

14 Arivazhagan, S., Ganesan, L., Subash Kumar, T.G., A modified statistical approach for image fusion using wavelet transform, J. *SIViP* 3(2), (2009): 137–144 .

15 Cao, W., Li. B., Zhang, Y., A remote sensing image fusion method based on PCA transform and wavelet packet transform, *International conference on neural networks and signal processing*, Nanjing , 14-17 December , (2003): 976-981.

16 Cheng Y., Zhao R., Hu, F., Li Y., A novel algorithm of multi-sensor image fusion based on wavelet packet transform, *Journal of Electronics (China)*, 23(2), , (2006): 314-317.

17 Chen, H. , Liu ,Y.Y., Wang, Y.J., A Novel Image Fusion Method Based on Wavelet Packet Transform, *International Symposium on Knowledge Acquisition and Modelling Workshop*, (2008): 462-465.

18 Bao W., Wang,P., Romote sensing image fusion based on wavelet packet analysis, *IEEE 3rd International conference on Communication Software and Networks*, (2011): 359-362.

19 Shao-hui, C., Su Hongbo., Renhua, Z., Jing, T., Fusing remote sensing images using a` trous wavelet transform and empirical mode decomposition, *Pattern Recognition Letters*, 29(3), (2008):330–342.

20 Ghahremani, M., Ghassemian, H., Remote sensing image fusion using improved ATW-PCA transform, *Iranian Conference on Electrical Engineering, (2003):*1-6.

21 Kaplan, N.H., An additive empirical mode decomposition based method for the fusion of remote sensing images, *International Conference on Recent advances in Space Technologies*, (2014): 165-169.

22 Steffen, P., Heller, P.N., Gopinath, R.A., Burms, C.S., Theory of Regular M-Band Wavelet Bases, IEEE transaction on signal processing, 41(2), (1993): 3497-3511.

23 Nizam, S. Telatar, Z., Multispectral image fusion based on the Multiwavelet and IHS transforms, S*ignal Processing and Communications Applications Conference*, Muga,18-20 April (2012) :1-4.

24 Starck, J.L., Candès, E.J., Donoho, D.L., The Curvelet Transform for Image Denoising, *IEEE Trans. On Image Processing*, (11) 6, (2002): 670-684.

25 Choi, M., Kim, R.Y., Nam, M.Y., Kim, H.O., Fusion of multispectral and panchromatic Satellite images using the curvelet transform, *IEEE Geoscience and Remote Sensing Letters*, 2(2) ,(2005): 136-140 .

26 Nencini, F., Garzelli, A., Baronti, S., Alparone, L., Remote sensing image fusion using the curvelet transform, *Information Fusion*, 8(2), (2007): 143–156.

27 Do, M., Vetterli, M., The contourlet transform: An efficient directional multiresolution image representation, *IEEE Trans. Image Process,* 14, (2005): 2091–2106.

28 Shu ,Z., Zhijun, L., ; Liu, G., Zhong, R., Gan, L., Remote sensing image fusion based on wavelet-based contourlet packet, *International conference on Environmental Science and Information Application Technolog*y, 2, (2010): 112-115.

29 Zhou ,J., Cunha, A.L. Do, M.N., Nonsubsampled contourlet transform: construction and application in enhancement, *International conference on image processing*, 1, (2005), 1469-1472.

30 Yang, X.H., Jiao, L.C., Fusion Algorithm for Remote Sensing Images Based on Nonsubsampled Contourlet Transform, *Acta Automatica Sinica*, 34(3), (2008):274-281.

31 Yi-quan, W.U., Chao,W.U., , Shi-hua, W.U., Fusion of Remote Sensing Images Based on Nonsubsampled Contourlet Transform and Region Segmentation, *Journal of Shanghai Jiaotong University (Science)*, 16(6), (2011): 722-727.

32 Selesnick, I.W., Abdelnour, A.F., Symmetric Wavelet Tight Frame with two generators, *Applied and Computational Harmonic Analysis*, 17, (2004): 211-225..

33 Selesnick, I.W., A Higher Density Discrete Wavelet Transform, *IEEE Transactions on signal procesing*, 54 (8), (2006): 30239-3048.

34 Hadeel,N., Taai.A.l., A Novel Fast Computing Method for Framelet Coefficients. American Journal of Applied Sciences, 5(11), (2008): 1522-1527.

35 Sulochana,S. Vidhya,R., High Resolution Image Fusion based on Feature Motivated Pulse Coupled Neural Networks (PCNN) in Framelet Transform Domain, *International Journal of earth sciences and Engineering*, (2013): 291-296.

36 Teggi, S., Cecchi, R., Serafini,F., TM and IRS-1C-PAN data fusion using multiresolution decomposition methods based on the 'a trous' algorithm, *International Journal of Remote Sensing*, 24,(2003): 1287-1301.

37 Gonzalez-Audicana, M., Garcia, R., Herrero-Isern, J., Fusion of multispectral and panchromatic images using new methods based on wavelet transforms- Evaluation of crop classification accuracy. *In Proceedings of 22nd EARSeL Annual Symposium*, (2002): 265-272.

38 Xu, H.Q., Study on data Fusion and classification of Landsat 7 ETM + imagery, *Journal of Remote Sensing*, 9(2), (2005): 186-194.

39 Colditz, R.R., Wehrmann, T., Bachmann, M., Influence of image fusion approaches on classification accuracy: a case study, *International Journal of Remote Sensing*, 27(15), (2006): 3311-3335.

40 Bruzzone, L., Carlin, L., Alparone, L., Baronti, S., Garzelli, A., Nencini, F., Can multiresolution fusion techniques improve classification accuracy:, *Proceedings of the Society of Photo-optical Instrumentation Engineers, Image and Signal Processing for Remote Sensing XII*, 6365,(2006), 1-12.

41 Roberts, J.W., Van Aardt, J.A., Ahmed, F.B., Assessment of image fusion procedures using entropy, image quality, and multispectral classification, *Journal of Applied Remote Sensing*, 2 (1), (2008).

42 Shuang, Li , Zhilin, Li, Effects of image fusion algorithms on classification accuracy, *International conference on Geoinformatics*, Beijing, (2010): 1-6.

43 Lalit Kumar., Priyakant Sinha ., Subhashni Taylor., Improving image classification in a complex wetland ecosystem through image fusion techniques, *Journal of applied Remote Sensing*, 8(1):(2014).

44 Michael E.Wall., Andreas Rechtsteiner., Luis, M., Rocha., *Singular value decomposition and principal component analysis;in A practical approach to micro array data analysis* (D.P. Berrar, W. Dubitzky, M. Granzow, eds.) Kluwer: Norwell, MA, (2003): 91-109.

45 Wei Liu., Jie Huang., Yongjun Zhao., Image Fusion Based on PCA and Undecimated Discrete Wavelet Transform, *Neural Information Processing Lecture Notes in Computer Science* , 4233, (2006): 481-48

46 Canny, J., A Computational Approach to Edge Detection .*IEEE Transactions on Pattern Analysis and Machine Intelligence,* 8(6), (1986): 679-698,

47 Meer,P., Georgescu,B., Edge Detection with Embedded Confidence. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 23(12), (2001): 679-698.

48 Kitchen, L., Rosenfeld, A., Edge Evaluation using Local Edge Coherence. *IEEE Transactions on Systems, Man and Cybernetics*, 11(9), (1981): 597-605.

49 Manjusha Deshmukh., Udhav Bhosale., Image Fusion and Image Quality Assessment of Fused Images, *International Journal of Image Processing(IJIP)*,4,(2010):484-508, 2010

50 Wang, Z., Bovik., A.C., A universal image quality index, *IEEE Signal Processing Letters*, 9(3), (2004): 81-84.

51 Mohsin, M.K., No Reference image quality assessment depending on YCbCr and L*u*v. European Scientific Journal, 9(10), (2013).

52 Wang, Z., Sheikh, H.R., Bovik, A.C., No-Reference Perceptual Quality Assessment of JPEG Compressed Images, *IEEE International Conference on Image Processing*, 1, (2002): 1477-1480.