



Study of Image Fusion on Satellite Images

Sudha.V¹, Priya.R²

¹Assistant Professor, Department of Computer Science, Dr.R.V.Arts and Science College, Karamadai

²Assistant Professor, Department of Computer Science, Dr.R.V.Arts and Science College, Karamadai

Abstract: The image fusion is one of the emerging advanced technology in the field of research. It is mostly used for challenges of Face Recognition. Image fusion is the combination of two or more source images which vary in resolution or image capture technology into a single composite representation. The main objective of an image fusion algorithm is to integrate the redundant and complementary information obtained from the satellite images in order to form a new image which provides a better description of the scene for human or machine perception. In this paper, we used a method based on the curvelet transform which represents edges better than wavelets. Since edges play a important role in image understanding and also enhances spatial resolution to enhance the edges. Curvelet-based image fusion method provides wider information in the spatial and spectral domains simultaneously.

Keywords: Principal Component Analysis , Eigen faces, empirical mean, peak signal to noise ratio (PSNR), Fusion, Multiresolution analysis, Wavelet transform, Curvelet transform

I. INTRODUCTION

Image fusion produces a single image by combining information from a one or more source images together, using pixel information, and feature or decision level techniques. The image fusion is one of the emerging advanced technologies in the field of research. It is mostly used for challenges of Face Recognition. Image fusion is the combination of two or more source images which vary in resolution or image capture technology into a single composite representation. The main objective of an image Fusion algorithm is to integrate the redundant and complementary information obtained from the satellite images in order to form a new image which provides a better description of the scene for human or machine perception. Image fusion is most important task for computer vision and robotics systems in which fusion results can be used in further processing steps for a given task. Image fusion techniques are practical and useful for many applications, including medical imaging, security, military, remote sensing, digital camera and consumer use. The fusion of high-spectral but low spatial resolution multispectral and low-spectral but high spatial resolution panchromatic satellite images is a most important application of remote sensing. Recently, wavelet-based image fusion method provides high quality of the spectral content of the fused image. However, Brovey, IHS, and PCA fusion methods have high spatial resolution when compared to wavelet-based fusion method. The image fusion is one of the applications of sensor technology. An important domain is the multi-resolution image fusion (commonly referred to pan-sharpening) which is used in remote sensing. Satellite images are of two types

- **Panchromatic images** - An black and white image collected in the broad visual wavelength range.
- **Multispectral images** - Images are of a different spectral band optically and acquired in more than one spectral or wavelength interval.

The SPOT PAN satellite provides high resolution (10m pixel) panchromatic data and the LANDSAT TM satellite provides low resolution (30m pixel) multispectral images. Image fusion combines these images and produces a single high resolution multispectral image.

The standard merging techniques of image fusion are based on Red-Green-Blue (RGB) to Intensity-Hue-Saturation (IHS) transformation. The steps that involved in satellite image fusion are as follows:

1. Resize the low resolution multispectral images to the same size as the panchromatic image.
2. Transform the R, G and B bands of the multispectral image into IHS components.
3. Modify the panchromatic image w.r.t the multispectral image by histogram matching of the panchromatic image with Intensity component of the multispectral images as reference.
4. Replace the intensity component and perform inverse transformation on the panchromatic image to obtain a high resolution multispectral image.

In this paper, we used a method based on the curve let transform which represents edges better than wavelets. Since edges play a important role in image understanding and also enhances spatial resolution to enhance the edges. Curve let-based image fusion method provides wider information in the spatial and spectral domains simultaneously.

II. STUDY ON IMAGE FUSION

2.1 WHY IMAGE FUSION IS REQUIRED?

The fused image contains greater information content for the scene than any one of the individual image sources alone. The reliability and overall detail of the image is increased, because of the addition of analogous and complementary information. Image fusion requires that



images be registered first before they are fused. Data fusion techniques combine data from different sources together. The main objective of employing fusion is to produce a fused result that provides the most detailed and reliable information possible. Fusing multiple information sources together also produces a more efficient representation of the data. [6].

2.2 TYPES OF IMAGE FUSION

There are three main categories of fusion:

- a. Pixel / Data level fusion
- b. Feature level fusion
- c. Decision level fusion

2.2.1 PIXEL LEVEL IMAGE FUSION

Pixel level fusion is the combination of the raw data from multiple source images into a single image. In pixel level fusion the fused pixel is derived from a set of pixels in the various inputs. The main advantage of pixel level fusion is that the original measured quantities are directly involved in the fusion process [8].

2.2.2 FEATURE LEVEL IMAGE FUSION

Feature level fusion deals with the fusion of features such as edges or texture while decision level fusion corresponds to combining decisions from several experts.

In other word, Feature level fusion requires the extraction of different features from the source data before features are merged together.

2.2.3 DECISION LEVEL IMAGE FUSION

Decision-level fusion is carried on sensor images. For Examples decision level Fusion methods include weighted decision methods, classical inference, Bayesian inference, and Dempster–Shafer method. In decision level fusion, the output obtained from multiple algorithms are combined together to yield a final fused decision.

2.3 ADVANTAGES OF IMAGE FUSION

- Improve reliability (by redundant information) [8].
- Improve capability (by complementary information) [8].

III. REVIEW ON SOME IMPORTANT TERMS AND CONCEPTS

3.1 WAVELET TRANSFORM

A wavelet is represented by square-integral function orthonormal series generated by a wavelet. Nowadays, wavelet transformation is one of the most applied time-frequency-transformations. The wavelet function is $\phi(x,y) = \phi(x-ba) * \phi(x-ba)$

3.2 DIGITAL CURLET TRANSFORM

Curvelets are a non-adaptive technique for multi-scale object representation. Being an extension of the wavelet concept, they are becoming popular in similar fields, namely in image processing and scientific

computing. Wavelets generalize the Fourier transform by using a basis that represents both location and spatial frequency. For 2D or 3D signals, directional wavelet transforms go further, by using basis functions that are also localized in orientation. A curvelet transform differs from other directional wavelet transforms in that the degree of localization in orientation varies with scale. In particular, fine-scale basis functions are long ridges; the shape of the basic functions at scale j is 2^{-j} by $2^{j/2}$ so the fine-scale bases are skinny ridges with a precisely determined orientation.

Curvelets are an appropriate basis for representing images (or other functions) which are smooth apart from singularities along smooth curves, where the curves have bounded curvature, i.e. where objects in the image have a minimum length scale. This property holds for cartoons, geometrical diagrams, and text. As one zooms in on such images, the edges they contain appear increasingly straight. Curvelets take advantage of this property, by defining the higher resolution curvelets to be more elongated than the lower resolution curvelets. However, natural images (photographs) do not have this property; they have detail at every scale. Therefore, for natural images, it is preferable to use some sort of directional wavelet transform whose wavelets have the same aspect ratio at every scale.

When the image is of the right type, curvelets provide a representation that is considerably sparser than other wavelet transforms. This can be quantified by considering the best approximation of a geometrical test image that can be represented using only n wavelets, and analysing the approximation error as a function of n . For a Fourier transform, the squared error decreases only as $O(1/n)$. For a wide variety of wavelet transforms, including both directional and non-directional variants, the squared error decreases as $O(1/n)$. The extra assumption underlying the curvelet transform allows it to achieve $O((\log n)^3/n^2)$.

Efficient numerical algorithms exist for computing the curvelet transform of discrete data. The computational cost of a curvelet transform is approximately 10–20 times that of an FFT, and has the same dependence of $O(n^2 \log n)$ for an image of size $n*n$.

3.3 DISCRETE RIDGELET TRANSFORM (DRT)

This of course suggests that approximate Radon transforms for digital data can be based on discrete fast Fourier transforms. In outline, one simply does the following,

3.3.1 2D-FFT

Compute the two-dimensional Fast Fourier Transform (FFT) of f .

3.3.2 Cartesian to polar conversion

Using an interpolation scheme, substitute the sampled



values of the Fourier transform obtained on the square lattice with sampled values of f^* on a polar lattice: that is, on a lattice where the points fall on lines through the origin.

Variance is the measure of the variability or spread of data in a data set. In fact it is almost identical to the standard deviation. Variance is simply the standard deviation squared. The formula is this: [7]

$$var(X) = \frac{\sum_{i=1}^n (X_i - \bar{X})(X_i - \bar{X})}{(n - 1)}$$

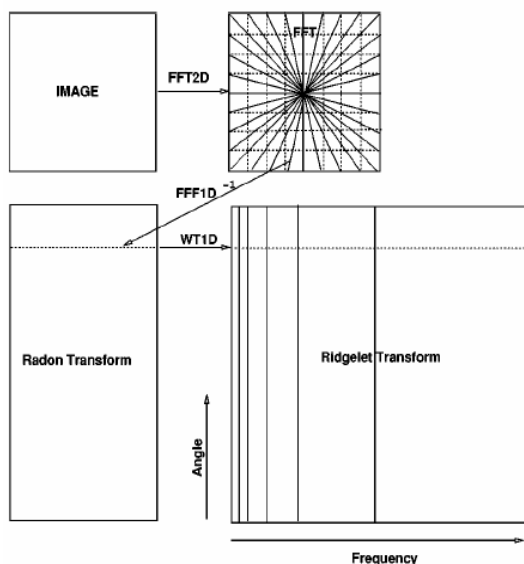


Figure 1. Ridgelet transform flow graph.

Each of the $2n$ radial lines in the Fourier domain is processed separately. The 1-D inverse FFT is calculated along each radial line followed by a 1-D non orthogonal wavelet transform. In practice, the 1-D wavelet coefficients are directly calculated in the Fourier space.

Curvelets are based on multiscale ridgelets combined with a spatial band pass filtering operation to isolate different scales. This spatial band pass filter nearly kills all multiscale ridgelets which are not in the frequency range of the filter. In other words, a curvelet is a multiscale ridgelet which lives in a prescribed frequency band. The bandpass is set so that the curvelet length and width at fine scales are related by a scaling law $width \propto length^2$ and so the anisotropy increases with decreasing scale like a power law. There is very special relationship between the depth of the multiscale pyramid and the index of the dyadic subbands; the side length of the localizing windows is doubled at every other dyadic subband.

3.4 EIGEN VECTORS AND EIGEN VALUES

An eigenvector of a matrix is a vector such that, if multiplied with the matrix, the result is always an integer multiple of that vector. This integer value is the corresponding eigenvalue of the eigenvector. This relationship can be described by the equation $M \times u = \lambda \times u$, where u is an eigenvector of the matrix M and λ is the corresponding eigen value.

3.5 VARIANCE

3.6 EMPIRICAL MEAN

The mean subtracted is the average across each dimension. So, all the x values have x' (the mean of the x values of all the data points) subtracted, and all the y values have y' subtracted from them. For example, if we have a matrix of 3×2 , then the empirical mean will be of dimension 1×2 . [7]

3.7 PRINCIPAL COMPONENT ANALYSIS (PCA)

The PCA involves a mathematical procedure that converts a number of correlated variables into a number of uncorrelated variables called principal components. It computes a compact and optimal description of the data set. The first principal and succeeding component accounts for as much of the variance in the data. First principal component is taken to be along the direction with the maximum variance. The second principal component is constrained to lie in the subspace perpendicular of the first. Within this subspace, this component points the direction of maximum variance. The third principal component is taken in the maximum variance direction in the subspace perpendicular to the first two and so on. The PCA is also called as Karhunen-Loève transform or the Hotelling transform. The PCA does not have a fixed set of basis vectors like FFT, DCT and wavelet etc. and its basis vectors depend on the data set.

3.8 PEAK SIGNAL TO NOISE RATIO (PSNR)

PSNR computes the peak signal-to-noise ratio, in decibels, between two images. This ratio is used as a quality measurement between the original and a reconstructed image. The higher the PSNR, the better is the quality of the reconstructed image. To compute the PSNR, first we have to compute the mean squared error (MSE) using the following equation:

$$MSE = \sum_{m, n} [I_f(m, n) - I_r(m, n)]^2 / M * N$$

IV. IMPLEMENTATION DETAILS OF THE PROPOSED ALGORITHM

4.1 PROPOSED ALGORITHM

- The original three multispectral images are obtained from the database.
- Three input images $I_1(x, y)$, $I_2(x, y)$ and $I_3(x, y)$ are produced, whose histograms are specified



according to histograms of multi-spectral images R,G,B respectively.

- By using well-known wavelet-based image fusion method, fused images I_1+R, I_2+G and I_3+B are obtained.
- $I_1(x, y)$, $I_2(x, y)$ and $I_3(x,y)$ are decomposed into subbands by applying filtering algorithm
- Each image is replaced by fused image which obtained from wavelet-based image fusion method.
- The ridgelet transform is then applied to each block.
- Curvelet coefficients (or ridgelet coefficients) are modified to obtain enhance edges in the fused image.
- The Curvelet reconstructions are carried out for I_1 , I_2 , and I_3 , respectively. Three new images (F_1 , F_2 , and F_3) are then obtained, which reflect the spectral information of the original multi-spectral images R, G, and B, and also the spatial information of the pan image.
- F_1 , F_2 , and F_3 are combined into a single fused image F .

In this approach, we can obtain an optimum fused image which has richer information in the spatial and spectral domains simultaneously. Therefore, we easily can find out small objects in the fused image and separate them. This is the reason why curvelets-based image fusion method is very efficient for image fusion.

4.2 PERFORMANCE ANALYSIS

From the fused image in below Figure, it should be noted that both the spatial and the spectral resolutions have been enhanced, in comparison to the original images. The spectral information in the original panchromatic image has been increased, and the structural information in the original multispectral images has also been enriched. Hence, the fused image contains both the structural details of the higher spatial resolution panchromatic image and the rich spectral information from the multispectral images.

4.2.1 EXPERIMENTAL RESULTS

Original Satellite Image

- a. Wavelet Based Fusion
- b. Curvet Based Fusion

4.2.2 QUANTITATIVE ANALYSIS

The combination entropy (C.E.) shows the property of combination between images. In Table, the combination entropy of the curvelet-based image fusion is greater than those of other methods. Thus, the curvelet-based

image fusion method is better than the wavelet and IHS methods in terms of combination entropy. The mean gradient (M.G.) reflects the contrast between the details variation of pattern on the image and the clarity of the image. The combination entropy (C.E.) shows the property of combination between images. In Table, the combination entropy of the curvelet-based image fusion is greater than those of other methods. Thus, the curvelet-based image fusion method is better than the wavelet and IHS methods in terms of combination entropy.

TABLE I. A COMPARISON OF IMAGE FUSION BY THE WAVELETS, THE CURVELETS, AND IHS METHODS

Method	C.E	M.G	C.C
Original Images (R,G,B)	9.5632	20.9771 22.2667 21.6789	
Image fused by Wavelet (F1, F2, F3)	22.3452	22.7275 23.7696 23.9975	0.9261 0.9196 0.8690
Image fused by Curvelet (F1, F2, F3)	26.9948	25.8385 26.9576 28.4971	0.9457 0.9463 0.9289
Image fused by HIS (F1, F2, F3)	16.5482	23.4475 23.6813 23.7283	0.9692 0.9951 0.9581

V. CONCLUSION

A newly developed method based on the curvelet transform is used for fusing satellite images. In this paper, an experimental study was conducted by applying the proposed method, and also other image fusion methods, for fusing satellite images. A comparison between the wavelet, curlet and IHS method was made and image fusion is obtained. Based on the experimental results respecting the four indicators—the combination entropy, the mean gradient, and the correlation coefficient, the proposed method provides a good result, both visually and quantitatively, for remote sensing fusion.

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