

Survey on Image Fusion Using Combination of Wavelet And Curvelet Fusion

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Abstract: Image Fusion is the process in which several images of the same scene are taken through sensors and information are combined from these images in order to achieve the best fused image which contains the best information coming from the source images. Image fusion requires that images be registered first before they are fused. Image Fusion makes it a lot of advantages on remote sensing, medicine, computer vision, military target detection and identification that it has overcome the blind spot in many fields of science and technical difficulties. Wavelet transform has an impressive reputation as a tool for image processing in image denoising and image fusion application. In the necessary of anisotropic transform, a multiresolution geometric analysis, named curvelet transform was proposed. Being the extension of wavelet, it did make a impressive performance in image denoising. The Curvelet transform is suited for objects which are smooth away from discontinuities cross curves. The idea of current research is to show the improvement in image processing parameters for image fusion application using curvelet transform and compare it with the wavelet and PCA method.

Keywords: Image Fusion, Wavelet Transform, Curvelet Transform, PCA method.

A. Introduction

Image fusion is a process of combining the relevant information from a set of images into a single image, where the resultant fused image will be more informative and complete than any of the input images. Image fusion produces a single image by using pixel, and feature or decision level techniques. The main aim of an image fusion algorithm is to take redundant and complementary information from the source images and to generate an output image with better visual quality. 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. Image Fusion makes it a lot of advantages on remote sensing, medicine, computer vision, military target detection and identification that it has overcome the blind spot in many fields of science and technical difficulties. Especially in computer vision, image

fusion technology has greatly improved the accuracy of the identification.

Image Fusion Method and Techniques

Image fusion methods are broadly classified into two groups:

- A. Spatial Domain
- B. Transform Domain

A. Spatial Domain

In Spatial domain fusion method image pixels play an important role, manipulations are done on image pixels to enhance the image quality. In these spatial variables i.e intensity of pixels is varied through some mathematical calculations, using techniques like maximum select where maximum intensity pixels are selected from set of source images and enhanced image is developed. Another way is by calculating mean values of pixels. Spatial domain image fusion techniques provide high spatial resolution. But the drawback of this technique is it produces spatial distortion and blur images when fused. Different Techniques which fall under this group are:

- Simple maximum
- Simple minimum
- Averaging
- Intensity-hue-saturation transform based fusion (IHS)
- Principal component analysis (PCA)

B. Transform Domain

In frequency domain fusion methods images are first sifted to frequency domain. Initially, images are applied into Fourier transform method and then that undergoes inverse Fourier transform method to get the resultant image. Therefore, the transformed coefficients (each corresponds to a transform basis) of an image are meaningful in detecting salient features. Spatial distortion problem or blurring problem which were encountered in spatial domain methods can be handled or rectified very well using transform domain as transformed coefficients provide appropriate information from source image which helps in constructing more accurate fused image. Different techniques of frequency domain are:

- Wavelet transform
- Curvelet transform
- Contourlet Transform
- Nonsampled Contourlet Transform

1. Principal Component Analysis(PCA)

Principal Component analysis is majorly done for techniques like image compression and image classification. Principal Component Analysis (PCA) is a vector space transform often used to reduce multidimensional data sets to lower dimensions for analysis. Using PCA transform, Principal components are derived by decomposing the the number of correlated variables into uncorrelated variables.

In this method, weighted average of Images to be fused is calculated. The weights for each source image are obtained from the Eigen vector related to the largest Eigen value of the covariance matrices of each source. The objective of PCA is to reduce dimensionality by extracting the smallest number of components that results for most of the variation in the original multivariate data and conclude the data with little loss of information which can be neglected to get the best resultant image. The first principal component is taken along the direction of the maximum variance. The second principal component is forced to lie in the subspace vertical (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 vertical to the first two and so on. The set of source image called as input images $I_1(x, y)$ and $I_2(x, y)$ are arranged in two column vectors to subtract their empirical means. The resulting vector has a dimension of $n \times 2$, where n is length of the each image vector. The eigen vector and eigen values for this resulting vector are computed and the eigen vectors corresponding to the larger eigen value obtained. The normalized components P_1 and P_2 (i.e., $P_1 + P_2 = 1$) are computed from the obtained eigen vector.

The fused image is: $I_f = P_1 I_1 + P_2 I_2$.

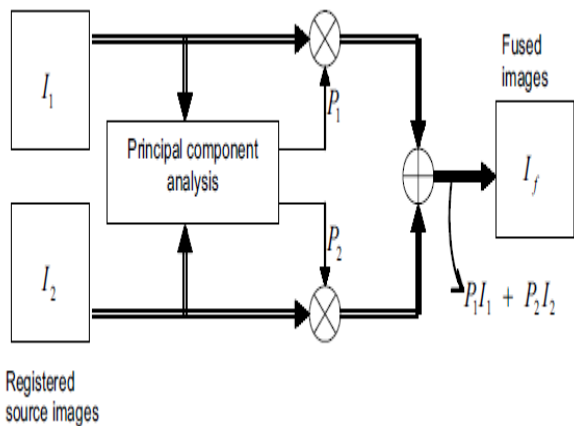


Figure:Image Fusion by PCA

2. Discrete Wavelet Transform(DWT)

Discrete wavelet transform is a multiscale (multiresolution) approach well suited to manage the different image resolutions. DWT decomposes the images in different kinds of coefficient which preserve the image information. Such coefficients coming from different images can be appropriately combined to obtain new coefficients, so that the information in the original images is collected appropriately. Wavelet theory is an extension of Fourier theory in many aspects and it is introduced as an

alternative to the short-time Fourier transform (STFT). In Fourier theory, the signal is decomposed into sines and cosines but in wavelets the signal is projected on a set of wavelet functions. Wavelet provide good resolution in both time and frequency domains. In wavelet analysis the signal is decomposed into scaled (dilated or expanded) and shifted (translated) versions of the chosen mother wavelet or function. A wavelet is a small wave that grows and decays essentially in a limited time period.using wavelet transform it is easy to compress ,analyze or transmit the input images.

Wavelet transformation provides time and frequency both representations. Wavelet transform decomposes a signal into a set of basic functions (wavelets). Wavelets are obtained from a single prototype wavelet $\Psi(t)$ called mother wavelet by shifting:

A wavelet to be a small wave, it has to satisfy two basic properties:

- Time integral must be zero

$$\int_{-\infty}^{\infty} \varphi(t) dt = 0$$

- Square of wavelet integrated over time is unity

$$\int_{-\infty}^{\infty} \varphi^2(t) dt = 1$$

The idea behind the Discrete Wavelet transform in image process is to multi differentially decompose the image into sub images in different spatial and frequency domain and transform the coefficient of sub-image. After the original image has been transformed, the next step is to decompose it in a 4 frequency ranges which is one low frequency district(LL) and three high-frequency districts(LH,HL,HH) as depicted in figure.

1, 2, 3-Decomposition level

L-Low frequency band

H-High frequency band

LL^3	LH^3	LH^2	LH^1
HL^3	HH^3	HL^2	
	HL^2	HH^2	HH^1
	HL^1		

Figure: Wavelet Decomposition

Wavelet separately filters and down samples the 2-D data (image) in the vertical and horizontal directions (separable filter bank). The input (source) image is $I(x, y)$ filtered by low pass filter L and high pass filter H in horizontal direction and then down sampled by a factor of two (keeping the alternative sample) to create the coefficient matrices $I_L(x, y)$ and $I_H(x, y)$.

The coefficient matrices $I_L(x, y)$ and $I_H(x, y)$ are both low pass and high pass filtered in vertical direction and down sampled by a factor of two to create sub bands (sub images) $I_{LL}(x, y)$, $I_{LH}(x, y)$, $I_{HL}(x, y)$, $I_{HH}(x, y)$. The $I_{LL}(x, y)$ contains the average image information

corresponding to low frequency band of multi scale decomposition. It could be considered as smoothed and sub sampled version of the source image $I(x, y)$. It represents the approximation of source image $I(x, y)$, $I_{LH}(x, y)$, $I_{HL}(x, y)$ and $I_{HH}(x, y)$, are detailed sub images which contain directional (horizontal, vertical and diagonal) information of the source image $I(x, y)$, due to spatial orientation. Multi-resolution could be achieved by recursively applying the same algorithm to low pass coefficients from the previous decomposition.

Notations

- ↓ C – Keep 1 column out of 2 (down samplings in columns)
- ↓ R – Keep 1 row out of 2 (down samplings in rows)
- X – Convolve with x, where x indicates block name

Figure: Image fusion using wavelet transform

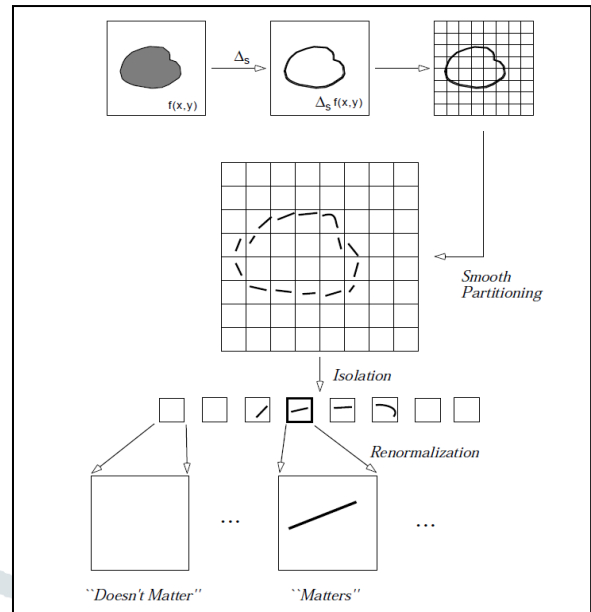


Figure: Overview of Organization of the Curvelet Transform

3. Curvelet Transform

The wavelet transform has proved itself as a impressive tool for mathematical analysis and signal processing but this technique is not so successful for directionality issues, although many successful upgradation on DWT technique has been done like complex DWT and dual tree complex DWT to rectify the problem of poor directionality but are still limited.

1999, an anisotropic geometric wavelet transform, named ridgelet transform, was proposed by Candes and Donoho, and is optimal at representing straight-line singularities. Unfortunately, global straight-line singularities are rarely observed in rare applications. In 2000, curvelet transform was introduced by Candes and Donoho which is suited for objects which are smooth away from discontinuities cross curves. Actually the ridgelet transform is the core spirit of the curvelet transform. To analyze local line or curve singularities, a natural idea is to consider a partition of the image, and then to apply the ridgelet transform to the obtained sub-images. Curvelet transform handles curve discontinuities well as they are designed to handle curves using only a small number of coefficients. Curvelet transform has several applications in various areas such as image denoising, image fusion etc. Curvelet transform has direction characteristic, and its base supporting session satisfies content anisotropy relation, except have multi scale wavelet transform and local characteristics. Curvelet transform can represent appropriately the edge of image and smoothness area in the same precision of inverse transform.

Later, a considerably simpler second-generation curvelet transform based on frequency partition technique was proposed.

Stages of The Curvelet Transform

1. Sub band decomposition
2. Smooth Partitioning
3. Renormalization
4. Ridgelet Analysis

1. Sub band decomposition

In this step, the image is decomposed into frequency subbands, without down sampling as in the traditional Wavelet transforms. Mathematically represented as

$$f(P_0 f, \rightarrow \Delta_1 f, \Delta_2 f, \dots)$$

$P_0 \rightarrow$ Lowpass filter

$\Delta_1, \Delta_2, \dots$ – Band-pass (high-pass) filters

2. Smooth Partitioning

It is define a collection of smooth window $w_Q(x_1, x_2)$ localized around dyadic squares:

$$Q_{(s, k_1, k_2)} = \left[\frac{k_1}{2^s}, \frac{k_1+1}{2^s} \right] \times \left[\frac{k_2}{2^s}, \frac{k_2+1}{2^s} \right] \in Q_s$$

Let w be a smooth windowing function with ‘main’ support of size $2^{-s} \times 2^{-s}$. Multiplying a function by the corresponding window function w_Q produces a result localized near $Q (\forall Q \in Q_s)$. Doing this for all Q at a certain scale, i.e. all $Q = Q(s, k_1, k_2)$ with k_1 and k_2 varying but s fixed, procedure, we apply this windowing dissection to each of the subbands isolated in the previous stage of the algorithm. And this step produces a smooth dissection of the function into ‘squares’.

3. Renormalization

For a dyadic square Q , let

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

denote the operator which transports and renormalizes f so that the part of the input supported near Q becomes the part

of the output supported near $[0,1] \times [0,1]$. In this stage of the procedure, each 'square' resulting in the previous stage is renormalized to unit scale:

4. Ridgelet Analysis

The ridgelet construction divides the frequency domain to dyadic coronae $|x| \in [2^s, 2^{s+1}]$. A ridge fragment needs only a very few ridgelet coefficients to represent it. The ridgelet element has a formula in the frequency domain:

$$\hat{\rho}_\lambda(\xi) = \frac{1}{2} |\xi|^{-\frac{1}{2}} (\hat{\psi}_{j,k}(|\xi|) \cdot \omega_{i,l}(\theta) + \hat{\psi}_{j,k}(-|\xi|) \cdot \omega_{i,l}(\theta + \pi))$$

where,

- $\omega_{i,l}$ are periodic wavelets for $[-\pi, \pi)$.
- i is the angular scale and $l \in [0, 2^{i-1}-1]$ is the angular location.
- $\psi_{j,k}$ are Meyer wavelets for \mathfrak{R} .
- j is the ridgelet scale and k is the ridgelet location.

B. Literature survey

Much of the work has been done in the field of image fusion using wavelet and curvelet fusion.

Shriniwas T. Budhewar (2014), described the implementation of image fusion algorithm using wavelet and curvelet transform, and compared the result with different algorithm, and proved by the comparison of wavelet and curvelet transform that the standard deviation value for the wavelet is higher which indicates that wavelet transform is efficient in representing the contrast information. Also, edges are sharper for curvelet based image than wavelet based image.

Sweta K. Shah and Prof. D.U. Shah (2014), In this paper it is concluded with the experimental results that image fusion method based on Stationary Wavelet Transform is remarkably better than Principal Component Analysis and Discrete Wavelet Transform and it is concluded that spatial domain method have blurring problem. The transform domain methods provide a high quality spectral content.

Kusum Rani, Reecha Sharma (2013), This paper presents a review on some of the image fusion techniques (simple average, simple minimum, simple maximum, PCA, DWT). Spatial domain image fusion techniques provide high spatial resolution. But spatial domain have image blurring problem. The Wavelet transforms provide a high quality spectral content. Combination of DWT and PCA provide better performance and improve the image fusion quality.

Tong-Zhang, (2011, IEEE) In this letter, it is proposed that a image denoising method based on Dual-Tree complex wavelet with ellipse windows thresholding combining anisotropic diffusion in image denoising algorithm, where the elliptic windows are used for different oriented sub bands in order to estimate the signal variances of noisy wavelet coefficients. Authors use the complex wavelet which has stronger directional ability and local 6 directional Wiener filter to get a "clearer image", then use "clearer image" guidance the diffusion function of anisotropic diffusion to reduce noise in the image

Huimin LU, Yujie Li, Yuhki Kitazono, Lifeng Zhang, Shiyuan Yang, and Seiichi Serikawa, (2010, IEEE), this paper introduces the multi-focus image fusion method, which is based on curvelet transform. The maximum local energy method is used to calculate the energy of two images. curvelet transform is used to extract the coefficients from source image, low frequency coefficients are selected by local energy, through a sliding window, obtained output the Maximum energy pixel information. High-frequency coefficients are obtained by absolute maximum method. Compared with wavelet transform method, this method can get better performance

GUO Chao-feng and LI Mei-lian, (2010, IEEE), Improved image denoising algorithm is proposed in this paper, which uses a piecewise cubic spline interpolation algorithm to reconstruct wavelet coefficients after denoising based on Modulus Maximum Principle first, and then recompose the image using the mallat algorithm. Using the piecewise cubic spline interpolation algorithm to denoise image, the image obtains higher SNRP and smaller MAE.

H. Hariharan, A. Koschan and M. Abidi, (2009 IEEE) In this paper, a data-driven and application independent technique is presented to combine focal information from different focal planes. Fusion is done on medial and peripheral curvelets and the fused image combines information from different focal planes, while extending the depth of field of the scene. And it is concluded that direct curvelet fusion method exhibits improved global sharpness.

C. Methodology

Proposed work consist of three main modules:

1. Spatial Domain Method

In this work based on principal component analysis have been done. Steps for Principle Component Analysis are

- Find Covariance matrix
- Compute Eigen Values and Eigen Vector
- Evaluating Principle components

2. Frequency Domain Method

A. Wavelet Transform: Steps are

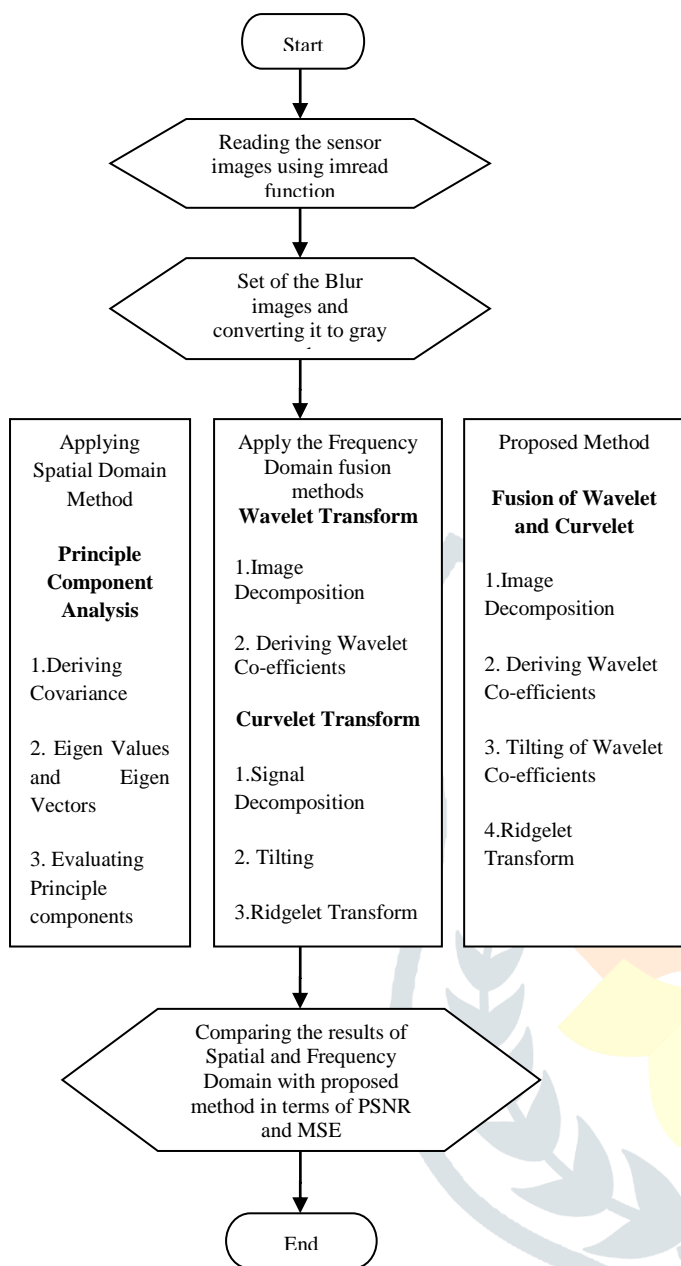
- Image Decomposition
- Deriving Wavelet Co-efficient.

B. Curvelet Transform: Steps are

- The image P is split up into three subbands P1, P2 and P3 using additive wavelet transforms.
- Tilting performed on subbands P1 and P2 by dividing the image into overlapping tiles
- Ridgelet Transform is performed on each tile of the subbands P1 and P2.

3. Fusion of wavelet and curvelet Transform

Flow of Proposed Work



D. Conclusion

Principal Component Analysis (PCA) has been most widely used method for dimensionality reduction and feature extraction. The discrete wavelet transform has become a very useful tool for fusion and the curvelet transform has evolved as a tool for the representation of curved shapes in graphical applications. The application of the curvelet transform in image fusion would result in better fusion results than that obtained using Principal Component Analysis (PCA) and Discrete wavelet transforms (DWT).

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