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# Mathematical method for contrast enhancement of remote sensing images using DT-CWT and PCA

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***Abstract:*** *Contrast enhancement is frequently referred to as one of the most important issues in image processing.One of the most important quality factors in satellite images comes from its contrast.Remote sensing image have played an important role in many field such as meteorology, agriculture, geology, education etc. One of the most important quality factors in satellite images comes from its contrast. As a rising demand for high quality remote sensing images contrast enhancement techniques are required for better visual perception and color reproduction. A novel contrast enhancement approach based on dual tree complex wavelet transform and principal component analysis is proposed . The proposed algorithm computes brightness-adaptive intensity transfer functions using the low-frequency luminance component in the wavelet domain and transforms intensity values according to the transfer function. More specifically, we first perform discrete wavelet transform (DWT) on the input images and then decompose the LL subband into low,middle,and high-intensity layers using the log-average luminance. Intensity transfer functions are adaptively estimated by using the knee transfer function and the gamma adjustment function based on the dominant brightness level of each layer. After the intensity transformation, the resulting enhanced image is obtained by using the inverse DWT. Although various histogram equalization approaches have been proposed in the literature, they tend to degrade the overall image quality by exhibiting saturation artifacts in both low and high intensity regions. The proposed algorithm overcomes this problem using the principal component analysis and dual tree complex wavelet transform.*

***Key Word:*** *contrast enhancement,DWT,Knee function,Gamma function,DT-CWT,PCA*

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## I. Introduction

Remote sensing images have played an important role in many fields such as meteorology, agriculture, geology, education, etc. As the rising demand for highquality remote sensing images, contrast enhancement techniques are required for better visual perception and color reproduction.The field of remote sensing and image processing are constantly evolving in the last decade. At present there are many enhancement techniques which are used for remote sensing image processing. The contrast of remote sensing images is low, which may include various types of noises. In order to make full use of remote sensing image information, the original image has to be enhanced. Histogram equalization (HE)[18]has been the most popular approach to enhancing the contrast in various application areas such as medical image processing, object tracking, speech recognition, etc. HE-based methods cannot, however, maintain average brightness level, which may result in either underor over saturation in the processed image. For overcoming these problems, bihistogram equalization (BHE)[2] and dualistic sub image HE[3] methods have been proposed by using decomposition of two sub histograms. For further improvement, the recursive mean-separate HE (RMSHE) [4] method iteratively performs the BHE and produces separately equalized sub histograms. However, the optimal contrast enhancement cannot be achieved since iterations converge to null processing. Recently, the gain-controllable clipped HE (GC-CHE)[5] has proposed. The GC-CHE method controls the gain and performs clipped HE for preserving the brightness. Demirel et al have also proposed a modified HE method which is based on the singular-value decomposition of the LL sub band of the discrete wavelet transform (DWT)[6].[7].In spite of the improved contrast of the image, this method tends to distort image details in low- and high-intensity regions. In remote sensing images, the common artifacts caused by existing contrast enhancement methods, such as drifting brightness, saturation, and distorted details; need to be minimized because pieces of important information are widespread throughout the image in the sense of both spatial locations and intensity levels. For this reason, enhancement algorithms for satellite images not only improve the contrast but also minimize pixel distortion in the low- and high-intensity regions. To achieve this goal, present a novel contrast enhancement method for remote sensing images using dual tree complex wavelet tramsform and principal component analysis .

**Dual tree complex wavelet transform**

In spite of its efficient computational algorithm and sparse representation, the wavelet transform suffers from four fundamental, intertwined shortcomings.

**Oscillations**

Since wavelets are bandpass functions, the wavelet coefficients tend to oscillate positive and negative around singularities (see Figures 1 and 2). This considerably complicates wavelet-based processing, making singularity extraction and signal modeling, in particular, very challenging . Moreover, since an oscillating function passes often through zero, we see that the conventional wisdom that singularities yield large wavelet coefficients is overstated. Indeed, as we see in Figure 1 , it is quite possible for a wavelet overlapping a singularity to have a small or even zero wavelet coefficient.Here, the test signal is a step edge

**Shift Variance**

A small shift of the signal greatly perturbs the wavelet coefficient oscillation pattern around singularities .Shift variance also complicates wavelet-domain processing; algorithms must be made capable of coping with the wide range of possible wavelet coefficient patterns caused by shifted singularities.

**Aliasing**

The wide spacing of the wavelet coefficient samples, or equivalently, the fact that the wavelet coefficients are computed via iterated discrete-time downsampling operations interspersed with non ideal low-pass and high-pass filters, results in substantial aliasing. The inverse DWT cancels this aliasing, of course, but only if the wavelet and scaling coefficients are not changed. Any wavelet coefficient processing (thresholding, filtering, and quantization) upsets the delicate balance between the forward and inverse transforms, leading to artifacts in the reconstructed signal.

**Lack of Directionality**

Finally, while Fourier sinusoids in higher dimensions correspond to highly directional plane waves, the standard tensor product construction of M-D wavelets produces a checkerboard pattern that is simultaneously oriented along several directions. This lack of directional selectivity greatly complicates modeling and processing of geometric image features like ridges and edges

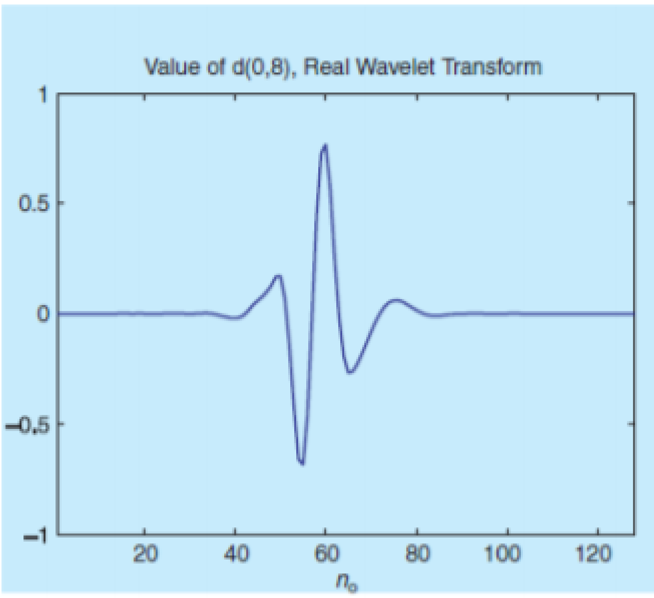


**Fig 1** Real DWT producing large and small wavelet coefficients

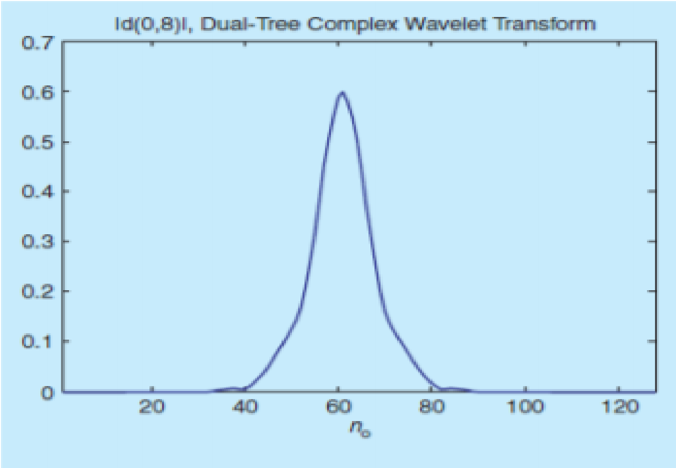


**Fig 2** Complex wavelet coefficient whose magnitudes are more directly related to their proximity to the edge

**Complex Wavelets**

Fortunately, there is a simple solution to these four DWT shortcomings. The key is to note that the Fourier transform does not suffer from these problems. First, the magnitude of the Fourier transform does not oscillate positive and negative but rather provides a smooth positive envelope in the Fourier domain. Second, the magnitude of the Fourier transform is perfectly shift invariant,with a simple linear phase offset encoding the shift. Third, the Fourier coefficients are not aliased and do not rely on a complicated aliasing cancellation property to reconstruct the signal; and fourth, the sinusoids of the M-D Fourier basis are highly directional plane waves. Unlike the DWT, which is based on real-valued oscillating wavelets, the Fourier transform is based on complex-valued oscillating sinusoids. The theory and practice of discrete complex wavelets can be broadly classed into two schools. The first seeks a $\psi c(t)$ that forms an orthonormal or biorthogonal basis. This strong constraint prevents the resulting CWT from overcoming most of the four DWT shortcomings outlined above. The second school seeks a redundant representation, with both $\psi r(t)$ and $\psi i(t)$individually forming orthonormal or biorthogonal bases. The resulting CWT is a 2× redundant tight frame in 1-D, with the power to overcome the four shortcomings.

**2D DTCWT Oriented Wavelets**

The M-D dual-tree CWT both maintains the attractive properties of the 1-D dual-tree and gains additional properties that make it particularly effective for MD wavelet-based signal processing. In particular, M-D dual-tree wavelets are not only approximately analytic but also oriented and thus natural for analyzing and processing oriented singularities like edges in images and surfaces in 3-D datasets. Although wavelet bases are optimal in a sense for a large class of 1-D signals, the 2-D wavelet transform does not possess these optimality properties for natural images.The reason for this is that while the separable 2-D wavelet transform represents point-singularities efficiently, it is less efficient for line-and curve-singularities (edges). Thus, one of the interesting avenues in wavelet-related research the development of 2-D multiscale transforms that represent edges more efficiently than the separable DWT. Examples include steerable pyramids directional FBs and pyramids curvelets and directional wavelet transforms based on complex FBs. These transforms isolate edges with different orientations in different subbands, and they frequently give superior results in image processing applications compared to the separable DWT.Typical wavelets associated with the 2-D separable DWT is shown in figure

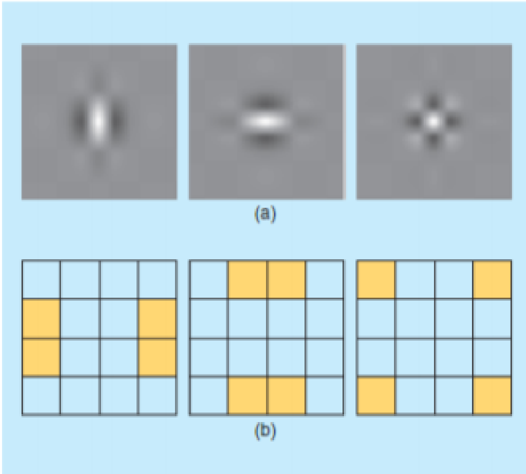


**Fig 3** Typical wavelets associated with the 2-D separable DWT

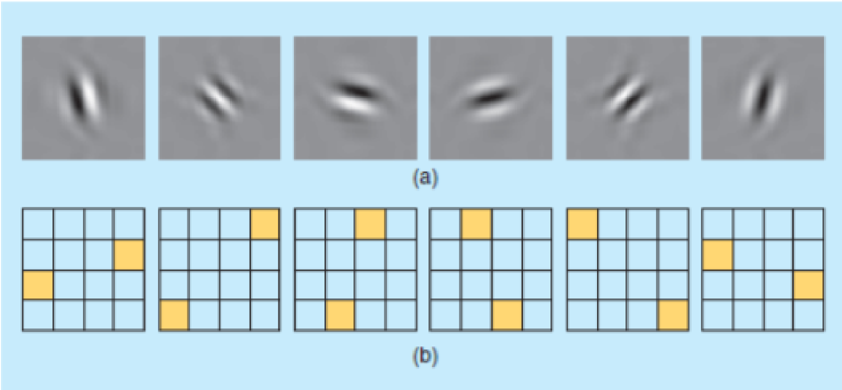


**Fig 4**
Wavelets in space domain b)Support of Fourier spectrum of each wavelet in the 2D frequency plane

**Principal Component Analysis PCA**

PCA is known a Principle Component Analysis this is a statistical analytical tool that is used to Explore sort and group data. PCA is a classical de-correlation technique which has been widely used for dimensionality reduction with direct applications in pattern recognition, data compression and noise reduction. What PCA does is take a large number of correlated (interrelated) Variables and transform this data into a smaller number of uncorrelated variables (principal Components) while retaining maximal amount of variation, thus making it easier to operate the data and make predictions. Or as Smith (2002) puts it PCA is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. Since patterns in data can be hard to find in data of high dimension, where the luxury of Graphical representation is not available; PCA is a powerful tool for analyzing data.

Steps in PCA

1. Get some data
2. Substract mean from each of the data dimensions
3. Calculate the covariance matrix
4. Calculate the eigen vectors and eigen values of covariance matrix,which provide information about patterns in the data
5. Choosing principal components and forming a feature vector

**Contrast Enhancement using DTCWT and PCA**

Contrast enhancement using DTCWT and PCA as shown in figure 5. The proposed algorithm decomposes the input image into six wavelet subbands and decomposes the LL subband into low-, middle-, and high-intensity layers by analyzing the logaverage luminance of the corresponding layer. The PCA algorithm is computed for each layer and all the contrast enhanced layers are fused with an appropriate smoothing, and the processed LL band undergoes the IDWT together with unprocessed subbands

Steps of Implementation

1. Apply DT-CWT to the input image
2. Find out the brightness level in LL subband using the Formula. Based on the brightness level LL subband decomposes Into low, high and middle intensity layers 3. Finding the PCA for all corresponding layers. For this Convert each layer into one dimensional vector A = [X1, X2, X3, X4....] (i=1 to m*n) Where m = number of rows; n= number of columns; Finding the mean value using this formula

$$k = \frac{1}{m*n}\sum_{i=1}^{m*n} a_i$$

3. Subtract the mean
5. Calculate the covariance matrix.
6. Calculate the eigen vectors and eigen values of the covariance matrix
7. Finding Gaussian Factor with 5x5 Mask

$$h = \frac{1}{\sqrt{2\pi}} \mathrm{e}^{(x^2+y^2)/2}$$

8. Finding maximum value of Gaussian coefficient (s1) And Eigen values (s).Multiply s1 with s this value will be the enhanced Factor
9.Multiplying all sub bands with this enhanced factor. Then perform Fusion and IDT-CWT are discussed in earlier chapters.

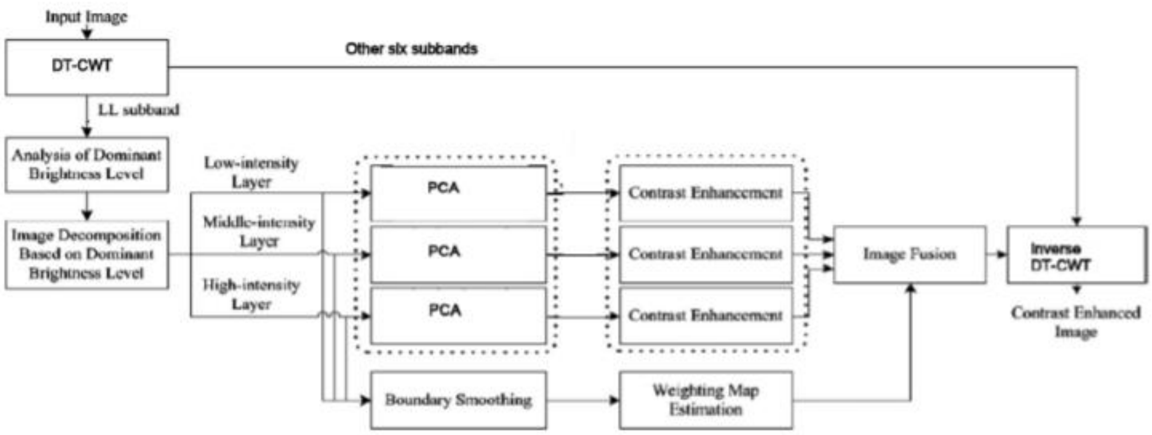


**Fig 5** Proposed method

## II. Results And Discussions

The results of the standard HE method show under- or over saturation artifacts because it cannot maintain the average brightness level. Although RMSHE and GC-CHE methods can preserve the average brightness level, and better enhance overall image quality, they lost edge details in low- and high-intensity ranges On the other hand, Demirels method could not sufficiently enhance the low-intensity range because of the singular-value constraint of the target image. show the results of the proposed contrast enhancement method. The overall image quality is significantly enhanced with preserving the average brightness level and edge details in all intensity ranges. Here the knee point is estimated using statistical methods. An alternate method for knee correction that is derivative method also tested with the same image.figure 5 shows the results of enhancement using DT CWT and PCA. Here four level DT CWT is used. The While wavelet-PCA can achieve the sharpest enhancement result compared to other enhancement methods. EMEvalues for diff erent enhancement methods are listed in Table I and it also includes the values of PSNR, MAE and MSE. Comparison of EME values show that the proposed Method outperforms existing enhancement methods.

| Methods | EME | MSE | PSNR | MAE |
|---|---|---|---|---|
| DTCWT-PCA | 1.3265 | 22.43 | 20.14 | 26.13 |
| Closed Loop Adaptation | 3.2683 | 21.13 | 19.12 | 24.13 |
| Alternate knee correction | 0.6347 | 27.43 | 24.12 | 28.14 |
| Adaptive intensity method | 0.7313 | 24.65 | 20.32 | 24.23 |
| SVD-DWT | 0.626 | 42.05 | 15.66 | 35.70 |
| RMSHE | 0.680 | 64.31 | 10.12 | 54.06 |
| BHE | 0.690 | 63.17 | 12.15 | 52.34 |
| HE | 0.689 | 42.17 | 15.54 | 37.92 |

Comparison of different contrast enhancement methods

**Fig 6** Orginal low contrast satellite image

**Fig 7** Contrast enhancement using proposed method

## III. Conclusion And Future Works

In this paper presented different contrast enhancement method for remote sensing images. The adaptive intensity transformation algorithm decomposes the input image into four wavelet subbands and decomposes the LL subband into low-, middle-, and high-intensity layers by analyzing the log-average luminance of the corresponding layer. The adaptive intensity transfer functions are computed by combining the knee transfer function and the gamma adjustment function. All the contrastenhanced Layers are fused with an appropriate smoothing, and the processed LL band undergoes the IDWT together with unprocessed, HL, and HH sub bands. Here the open loop adaptation is done. To avoid the drawback of open loop adaptation a new method called closed loop adaptation is proposed. Here LMS algorithm is used for the adaptive process. All these methods utilize discrete wavelet transform for image decomposition. It produces checker board artifacts. To avoid the draw backs of DWT a new transform called dual tree complex wavelet transform (DTCWT) is used. In the open loop adaptation adaptive intensity transfer function is estimated by knee transfer function and gamma adjustment function. The transfer function is applied for the every pixel of the image and It does not deals with which is more important once and lesser important once. To separate correlated and uncorrelated parts of an image a statistical method is used called principal component analysis (PCA).A new enhancement method is proposed based on DTCWT and PCA. Using this dimensionality reduction is also achieved and it can eff ectively enhance the overall quality and visibility of local details better than existing state-of-theart methods including RMSHE, GC-CHE and Demirels methods. This technique can be considered suitable for enhancement of low contrast satellite image with out changing original image quality completely.Experimental results demonstrate that the proposed algorithm can enhance the low-contrast satellite images and is suitable for various imaging devices such as consumer camcorders, real-time 3-D reconstruction systems, and computational cameras. Hence our future works second generation wavelets transforms can be used instead of DT CWT. And for the closed loop adaptation other adaptive algorithms such as RLS, LMS Newton can be used to obtain the faster convergence. By evaluating better EME values of other types of images, these algorithms are also applicable for the same. So we can develop a general enhancement for any types of images

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