Complex Wavelet Filter Bank Algorithm for Hyperspectral Mimetite Spectral Signature –Correlation Compared

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Abstract: The algorithm modified for complex wavelet based spectral signature values to find out the correlation for the first twenty samples of mimetite material .The data received from ISRO, research centre for different wavelength spectrum. The algorithm first considered for real wavelet and correlation is found. The same samples are made complex with the help of Hilbert transform to have the analytic signals The objective of this work is to extend and apply Wavelet based Dimension Reduction overmimetite spectral signature.

Keywords: *mimetite spectral signatures, dimension reduction, complex wavelet.*

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I. Introduction

The spectral signature contains the information about the substances and classes as per the wavelength.(Fig1)[20] compute results based on all the gathered information.

One way to approach this problem is to perform dimension reduction fig(2)[19] as pre-processing, i.e to apply a transformation that brings data from a high order dimension to a low order dimension.

II Dimension Reduction

Complex wavelet dimension reduction:
As a definition, data or dimension reduction is a process designed to reduce data volumes by filtering out redundant information.

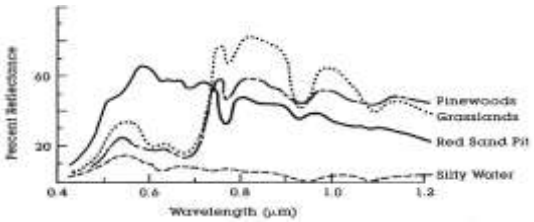

Fig1.example of spectral signature.

The new larger data volumes from hyperspectral sensors present a challenge for traditional processing techniques. Hyperspectral sensors provide much richer information than traditional processing techniques. Hyperspectral sensors provide much richer information than comparable multispectral sensors. However currently we do not have sufficient resources to

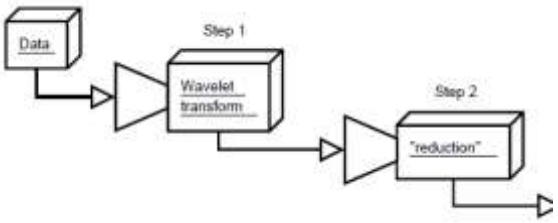

Fig 2: Depicting the reduction steps.

Algorithm:

The general description of the wavelet reduction algorithm follows:-
1)For each pixel in a hyperspectral scene, the 1-D signal corresponding to its spectral signatureis decomposed using a dual tree complex wavelet filter bank.(fig3)[21]
2)For each hyperspectral pixel, an approximation of the original spectrum is reconstructed using the synthesis filter bank. The proposed diagram would be reverse of analysis filter bank. The needed level of decomposition for a given pixel is the one that corresponds to producing an acceptable correlation with the original signature.

3) For each pixel in the hyperspectral scene and for each level of decomposition, the correlation between original and reconstructed signals is computed. All correlations higher than the user- specified threshold contribute to the histogram for that level of decomposition. When all pixels
are processed, the lowest level of wavelet decomposition needed to produce such correlation is used for the remainder of the algorithm. The correlation function between the original spectral signature (x) and its reconstructed approximation (y) is shown in
(Kaewpijit) et al ,2003 where N is the original dimension of the signal

$$\rho(x,y)=\frac{\sum x_i y_i-(\frac{1}{N})\sum x_i\sum y_i}{\sqrt{(\sum x_i^2-(\frac{1}{N})(\sum x_i)^2)(\sum y_i^2-(\frac{1}{N})(\sum y_i)^2)}}$$

Formula taken for the measure of correlation.
III About the complex wavelet based algorithm:

1)First the spectral signature values of mimetite material is considered for the one level of decomposition with the designed complex wavelet dual tree structures as in figure (3)[18]

2) The data is taken first as real values and with
2)The data is taken first as real values and with the algorithm mentioned, the correlation is found

2) The data is taken first as real values and with the algorithm mentioned ,the correlation is found between the original pixel spectral signature and reconstructed spectral signature.

3)Then the spectral signatures real values are converted into complex with the help of Hilbert transform.The one level decomposition is carried out with the imaginary part and correlation is again found out.

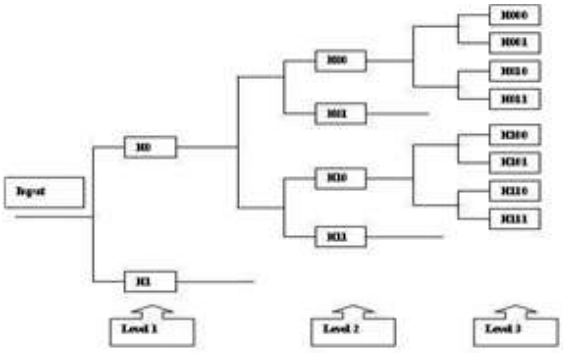

Fig 3: analysis complex filter bank

4)The total correlation is the average of both the values and this is an indication of similarity between the pixels.

5)The algorithm is tested on the spectral signatures received from ISRO,RRSSC,Nagpur.

Results and Analysis:

The following table is indicating the algorithm implementation for complex wavelet filter bank on the samples of spectral signatures of mimetite material .The samples were taken from the remote sensing centre and introduced in the designed complex filter bank for one level of decomposition .The reconstruction of the spectral signature is then implemented with the help of synthesis filter bank (Table 1)

Conclusion:

The correlation is an indicator of similarity between the spectral signatures. The paper has introduced the complex wavelet algorithm for the reduction process of the hyperspectral spectral signature. The correlation is improved with the complex consideration in the algorithm as compared to the existing algorithm for the wavelet based reduction method.

Wavelet Used	***Real part Correlation***	*imag part corr*	*Total corr*
Haar for First twenty spectral Sign	**0.9898**	0.9928	0.9913

Table 1: Simulation results

References

[1] J. A. Richards, Remote Sensing Digital Image Analysis An *Introduction*, 2nd ed. New York: Springer-Verlag, 1993
[2] D. W. Scott, "The curse of dimensionality and dimension reduction,"in *Multivariate Density Estimation: Theory, Practice, and Visualization*. New York: Wiley, 1992, ch. 7, pp . 195–217.
[3] R. H. Yuhas, A. F. H. Goetz, and J. W. Boardman, "Discriminationn among semi-arid landscape endmembers using the spectral angle mapper (SAM) algorithm," *Summaries 3rd Annu. JPL Airborne Geosci. Workshop*, June 1992, R. 0. Green Ed., Publ. 92-14, vol. 1, Jet Propulsion Laboratory, Pasadena, CA1992, pp. 147-149.
[4] M. 0. Smith, P. E. Johnson, and J. B. Adams, "Quantitative determination of mineral types and abundances from reflectance spectra using principal components analysis," in *Proc. 15th Lunar and Planetary Sei. Conf., Part 2, Geophys. Res.*, vol. 90, suppl.,pp. C797-C804, Feb. 15, 1985.
[5] 5] R. Nishii, S. Kusanobu and S. Tanaka, "Enhancement of Low Spatial Resolution Image Based on High ResolutionBands,"*IEEE Trans. on Geoscience and Remote Sensing*,
[6] K. Rasche, R. Geist, and J. Westall, "Detail preserving reproduction of color images for monochromats and

dichromats," IEEE Comput. Graph. Appl., vol. 25, no. 3, pp.22–30, May-June 2005.

[7] M. Ichikawa, K. Tanaka, S. Kondo, K. Hiroshima, K. Ichikawa , S. Tanabe, and K. Fukami, "Preliminary study on color modification for still images to realize barrier free color vision," in Proc. 2004 IEEE Int. Conf. Syst., Man, Cybern.,vol. 1, Oct. 2004, vol.34, no.5, pp.1151-1158, 1996.

[8] S. Haykin, Ed., *Advances in Spectrum Analysis and Array Processing, Volume II.*

[9] *Adaptive Filter Theory*, 2nd ed. Englewood Cliffs, NJ: Prentice- Hall, 1991.

[10] O. L. Frost III, ''An algorithm for linearly constrainedadaptive array processing,'' *Proc. IEEE* 60, 926–935 ,1972

[11] B. D. Van Veen and K. M. Buckley, ''Beamforming: aversatile approach to spatial filtering,'' *IEEE ASSP Mag.* , 4–24 Apr. 1998.

[12] C.-I. Chang and H. Ren, ''Linearly constrained minimum variancebeamforming for target detection and classification in hyperspectral imagery,'' in *IEEE Int. Geoscience and Remote Sensing Symp. '99*,pp. 1241–1243, Hamburg, Germany ,1999

[13] H. Ren, ''A comparative study of mixed pixel classification versuspure pixel classification for multi/hyperspectral imagery,'' M S Thesis,Department of Computer Science and Electrical Engineering, Universityof Maryland Baltimore County, Baltimore ,May 1998

[14] S. Haykin, *Adaptive Filter Theory*, 3rd. ed., Prentice-Hall, Englewood Cliffs, NJ ,1996.

[15] J. Harsanyi and C.-I. Chang, ''Hyperspectral image classification anddimensionality reduction: an orthogonal subspace projection approach,''*IEEE Trans. Geosci. Remote Sens.* **32**, 779–785 ~1994

[16] 1. C.-I. Chang and C. Brumbley, ''A Kalman filtering approach to multispectral image classification and detection of changes in signatureabundance,'' *IEEE Trans. Geosci. Remote Sens.* 257–268,1991

[17] D. E. Sabol, J. B. Adams, and M. 0. Smith, "Quantitative subpixelspectral detection of targets in multispectral images," ***J. Geophys.Res.,*** vol. **97,** pp. **2659-2672,** Feb. **25, 1992.**

[18] Shanti Swamy, Naresh kumar,S.D.Joshi, " A new method of estimating the signal matched dual tree complex wavelet filter bank ", IEEE International conference' Impact ' , AMU ,169,2009

[19] Jon Wickman," A wavelet approach to dimension reduction and classification of hyperspectral data," thesis submitted at university of Oslo ,May 2007.

[20] Randall b smith," A tutorial on hyperspectral imaging," Microimages Inc,USA.

[21] B Salehi and M J Valaden Joej," WAVELE-BASED REDUCTION OF HYPERSPECTRAL IMAGERY Department of remote sensing, Tehran.