

SATELLITE IMAGERY DIMENSIONALITY REDUCTION USING DISCRETE WAVELET TRANSFORM FOR THE EXTRACTION OF CADASTRAL FEATURES

Babawuro Usman¹,

Department of Computer Science,
Kano University of Science and Technology, Wudil

Adamu Mustapha²

Department of Geography,
Kano University of Science and Technology, Wudil

Abstract-*The Satellite imagery being naturally rich in information, careful information extraction is needed for the various applications that utilize it, as it is not suitable to be used in raw form because of the huge redundant information embedded therein. Therefore, satellite image dimensionality reduction is necessary in order to remove the unwanted information for further processing with less computational fatigue. This has made us to apply Discrete Wavelet Transform, to the High resolution satellite imagery so that it would contain less but more useful information for the extraction of cadastral features. Finally, having practically applied the 2D Discrete Wavelet Transform to the imagery, it has proved successful and made it more suitable for further cadastral analysis.*

Keywords-*Satellite Imagery, Discrete Wavelet Transform, Dimensionality Reduction, Cadastral analysis, Georectification*

I. INTRODUCTION

Diverse needs for land information and technological advancements have necessitated changes in land administration systems, which are then placing greater pressure on the ways and manners organizations operate [1]. Similarly, and more importantly, Cadastral survey should evolve for a more sustainable socio economic and environmental development, as stated by [2]. Therefore, the innovative research primarily aims at using comprehensive and integrated Digital Image Processing algorithmic formulations to extract representations of cadastral feature from High Resolution Satellite Imagery, HRSI data with minimum human interventions, as an alternative. Achieving that objective would necessitate the use of Discrete Wavelet Transform, DWT algorithms to reduce the dimensionality of the HRSI. In most cases, dimensionality reduction of the imagery data is required to enhance, among others, processing time and storage space as stated by Du H. et al. [3], that dimensionality reduction is an important pre-processing step in satellite imagery analysis, as it eliminates redundant bands and diminishes computational burden. Dimensionality reduction is an important task in processing HRSI because of its huge redundant information. It facilitates better classification, compression, and visualization of high-dimensional data by mitigating undesired properties of the high-dimensional space. Most of the techniques for dimensionality reduction are based on the intuition that data lies on or near a complex low-dimensional manifold that is embedded in the high-dimensional space [4]. The techniques for the reduction aim at identifying and extracting the much needed data from the high-dimensional space. Methods for dimensionality reduction, amongst others include Principal component analysis, Independent component analysis, Discrete Cosine Transform, DCT, Discrete Wavelet Transform, DWT.

In our case, dimensionality of the imagery is reduced by applying DWT independently to eliminate redundant information that could otherwise have the image to occupy more space and consume processing time. Unlike, the human eye that is limited to the visual band of electromagnetic, EM, spectrum, Digital image processing covers the entire EM spectrum, ranging from gamma to radio waves. It as well operates on images from other sources, such as images from ultrasound, electron microscopy, and other computer generated images [5][12]. This has made us to apply DWT, to the Satellite imagery so that we could be left with less but more useful information for our task. The paper concludes as follows. Section II Related works; Section III contains the mathematical background; Section IV contains the implementation details; Section V contains the practical results; Section VI has discussions while Section VII contains the conclusion.

II. RELATED WORKS

Several methods have been carried out for image dimensionality reduction. Though they differ technically but they do have the common goal of eliminating redundant information while retaining the much needed features for analysis. Patil S.R. et al. [4] used the method of principal component analysis, PCA, and reduced the redundant dimension of satellite imageries. They concluded that, though PCA is a lossy method, but it is effective. Ludovic J. et al. [6] presented in their study an objective comparison of several dimensionality reduction methods, by evaluating their capabilities to provide usable inputs to the K-means clustering algorithm classification using multispectral imageries. Their results show that linear methods run faster than non-linear but they provide images with relatively lower qualities as some demerits. Dutra da Silval R. et al. [7] in the course of achieving the goal used Wavelet transforms with two levels of decomposition for reducing the image. Antonio P. et al. [8] describe sequences of extended morphological transformations for filtering of high-dimensional remotely sensed hyper spectral datasets. Their approach is based on the concepts of mathematical morphology.

They revealed that, by designing morphological filters that take into account the complementary nature of spatial and spectral information, it is possible to achieve a good result. Considering the fact that each method suits some peculiar tasks, discrete wavelet transform for the dimensionality reduction of the HRSI is used in this work. It successfully reduces the imagery to a much lighter dimension while retaining the needed cadastral features for further analysis.

III. MATHEMATICAL BACKGROUND

Wavelet analysis has opened up many new information processing methods in HRSI. Wavelet is a mathematical function used to divide a given function or continuous-time signal into different scale components. A frequency range is assigned to each scale component. Each scale component is studied with a resolution that matches its scale. Thus the Wavelet is a multi-resolution representation function. Wavelet transform is the discrete sampling of the wavelets [9]. There are several choices of Wavelets including the Morlet wavelet, Daubechet wavelet, Har wavelet, et al. There are also variations as contained in [10]. If the image data is further transformed before encoding, then the compression scheme is called a Transform coding scheme. Commonly known examples are the DCT and the DWT. There are several reasons why it is better to encode the image in a transform-domain rather than directly in its spatial representation. First, the transformation de-correlates the image data and thus reduces inherent redundancy. Second, the representation in the transform domain is more closely related to the Human Visual System, HVS, perception structure [11] which gives it a natural sense. In this research we employed the DWT to dimensionally reduce the satellite imagery. The aim is to do space frequency localization for the imagery.

DWT syntax: Single-level discrete 2-D wavelet transform:

- $[cA, cH, cV, cD] = \text{dwt2}(X, \text{'wname'})$
- $[cA, cH, cV, cD] = \text{dwt2}(X, \text{Lo_D}, \text{Hi_D})$

The `dwt2` command performs single-level 2D wavelet decomposition with respect to either a particular wavelet or wavelet decomposition filters (`Lo_D` and `Hi_D`). $[cA, cH, cV, cD] = \text{dwt2}(X, \text{'wname'})$ computes the approximation coefficients matrix `cA` and details coefficients matrices `cH`, `cV`, and `cD` (horizontal, vertical, and diagonal), obtained by wavelet decomposition of the input matrix `X`. The `'wname'` string contains the wavelet name. $[cA, cH, cV, cD] = \text{dwt2}(X, \text{Lo_D}, \text{Hi_D})$ computes the 2D wavelet decomposition, based on wavelet decomposition filters that are specified, where `Lo_D` is the decomposition low-pass filter and `Hi_D` is the decomposition high-pass filter. `Lo_D` and `Hi_D` must have the same lengths. We employed the Dyadic partitioning technique as shown at Fig.3.1.

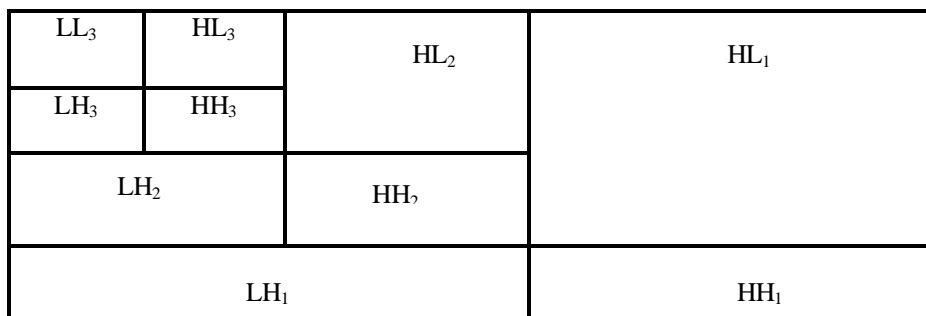


Fig. 3.1 Three levels decomposition showing the 10 sub bands of DWT

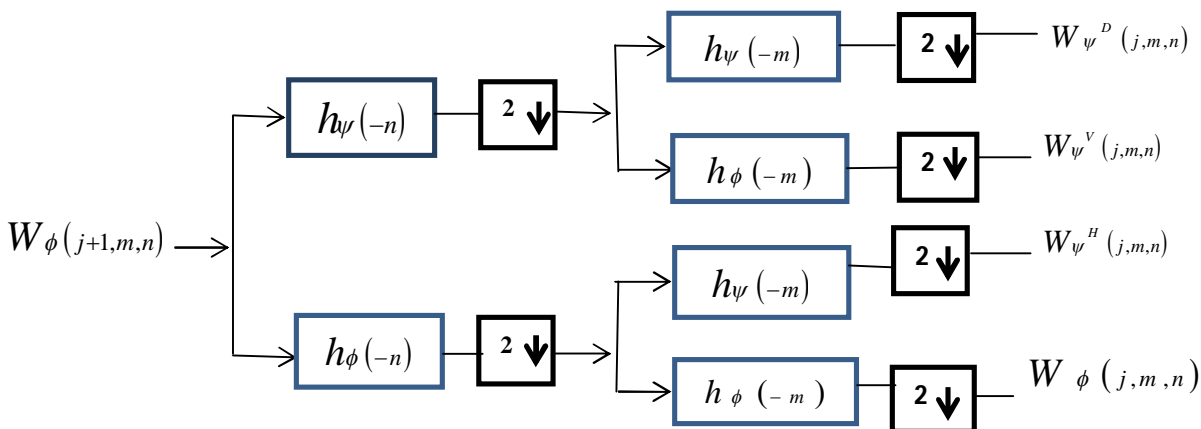


Fig.3.2 Cascaded analysis filter bank showing wavelet decomposition of an image

Where h_{ψ} and h_{ϕ} are the high pass (wavelet filter) and low pass filters (scaling filter); $j+1$ and j are scales, m , and n are the rows and columns indices. $W_{\phi}(j+1,m,n)$ is the original image and $W_{\phi}(j,m,n)$ is the approximate image obtained along LL portion of the image. $W_{\psi^D}(j,m,n)$, $W_{\psi^V}(j,m,n)$, and $W_{\psi^H}(j,m,n)$ are the detailed images along the diagonal, vertical and horizontal directions.

IV. IMPLEMENTATION

Satellite Imagery Dataset: The remote sensing image used in this study is a Quick Bird high resolution Satellite imagery with a 2.4m resolution, over a relatively flat landscape in Changsha city, Hunan province, China. This, imagery, 593X533, has a total number of pixel vectors, N , 316069. It is composed of a residential matrix textured with farmland patches of varying sizes and shapes which are excellent features with cadastral values. The three land-use classes dominating the scene are residential, agriculture and commercial. In this work, 2D DWT is used to reduce the imagery data, Fig. 4.2 to certain reasonable dimension at the same time retaining the relevant features needed for further image feature analysis. For more details refer to Fig.3.1 and Fig.3.2 which show how DWT decomposes the high resolution satellite imagery into sub-resolutions for better analysis.



Fig. 4.1 Rectified satellite imagery

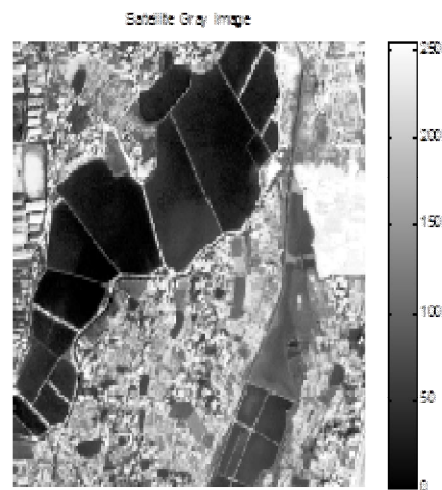


Fig 4.2 Gray scale Imagery of the Image

The HRSI contains cadastral features that are supposed to be extracted and analyzed. The following are the implementation steps

- 1: Replace each image column with its 1D DWT.
- 2: Replace each image row with its 1D DWT.
- 3: Repeat steps (1) and (2) on the lowest sub band to create the next scale.
- 4: Repeat step (3) until the desired number of scales has been created.

Using the three levels discrete wavelet transform, the input 2D signal, image, is decomposed into two frequency coefficients, the approximation coefficients as the low frequency part and the detail coefficients as the high frequency part. This is called wavelet decomposition. With higher level decompositions, multi resolution representation of the image is achieved. Conceptually, Fig.5.1 shows the wavelet decomposition of the satellite imagery. The other images, are the decompositions at higher levels from the satellite images as we can see visually. Fig.4.3 shows the flowchart of the whole process using discrete wavelet transform.

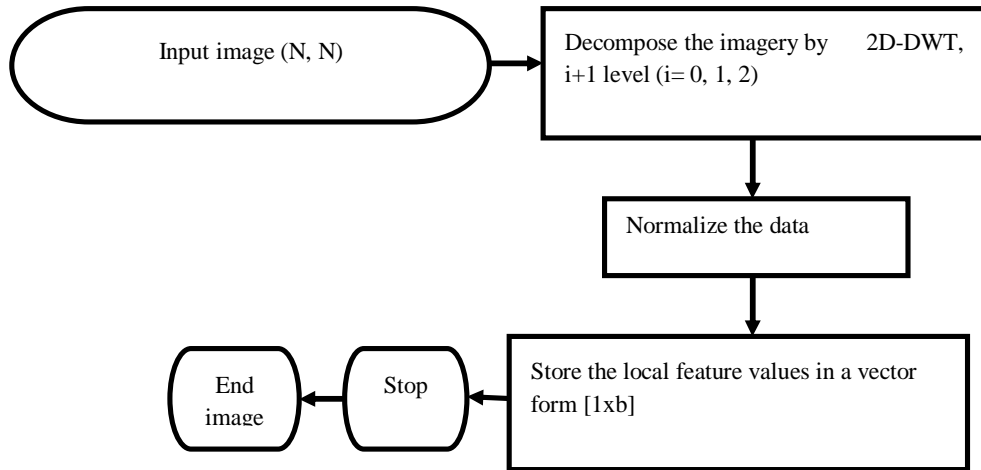


Fig.4.3 Flowchart of imagery dimensionality reduction using discrete wavelet transform

The wavelets decomposition provides the important information from the original data used for feature extraction and general image analysis. The data set, feature vectors, obtained by using DWT is processed. Practically Fig.5.1 shows the output of the HRSI having been processed with DWT.

V. PRACTICAL RESULTS/ OUTPUT

Dimentionality Reduction using DWT

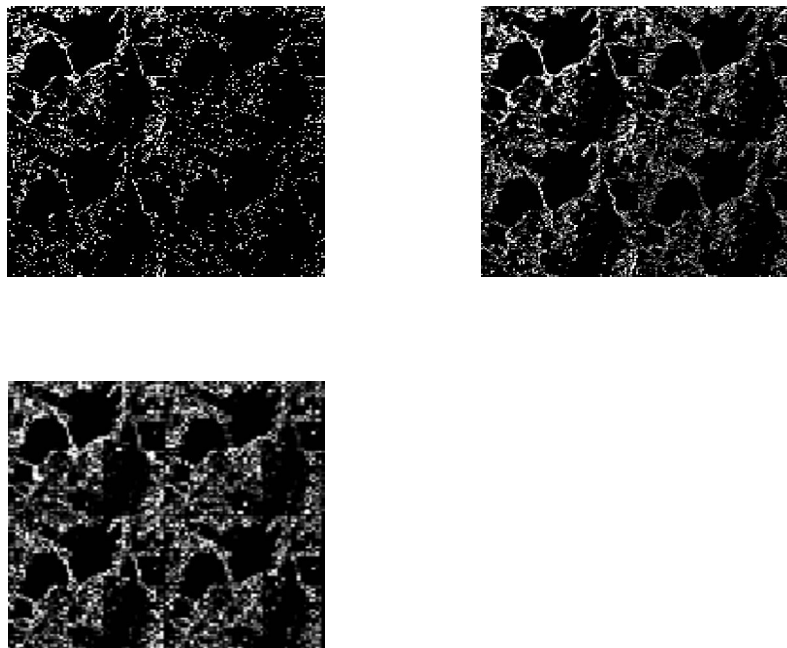


Fig.5.1 DWT decomposed Satellite Imagery

VI. DISCUSSIONS

Wavelets provide a framework of multi resolution representation of the Satellite imagery. One desirable characteristics of the wavelet transform is that the coefficients are nearly uncorrelated [13], i.e. the wavelet transformed image covariance matrix has off-diagonal terms nearly zero. Thus the wavelet coefficients are more effective than the original data as features. For each pixel in the sub images a feature vector can be constructed for further analysis. However, as we used down sampled sub bands in DWT, we are associated with certain disadvantages as highlighted by [11] as follows: Firstly, for each frequency level the decomposition contains typically 3 sub bands, representing the horizontal, vertical and diagonal details.

This limitation to just three orientations is necessary to avoid any data redundancy. The diagonal sub band contains both 45° and 135° directions. Consequently, as a demerit, these two orientations cannot be distinguished. Thus, an introduced distortion can either be oriented like the original signal or to its perpendicular. Secondly, the horizontal and vertical sub bands might encroach into the diagonal sub band. Depending on how broad the 1D-filters are in horizontal and vertical directions, the energy of the diagonal sub band can end up partially in the horizontal and vertical sub bands.

VII. CONCLUSION

Satellite imagery being naturally rich in information, information extraction is needed for the various applications including our task, as it is not suitable to be utilized in raw form because of the huge redundant information embedded therein. Therefore, image dimensionality reduction is necessary in order to remove the unwanted information for further processing with less computational fatigue. Hence the HRSI used in this paper is prepared for the effective and efficient extraction of the cadastral features therein.

ACKNOWLEDGEMENT

The authors express gratitude to Kano University of Science and Technology, KUST, Wudil, Mrs. Aishat Ayuba and Mrs. Asiya Isa Muhd for their unalloyed technical and nontechnical supports.

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