ISSN (Online) : 2319 - 8753
ISSN (Print) : 2347 - 6710

International Journal of Innovative Research in Science, Engineering and Technology

Volume 3, Special Issue 3, March 2014

2014 International Conference on Innovations in Engineering and Technology (ICIET'14)
On 21st & 22nd March Organized by

K.L.N. College of Engineering, Madurai, Tamil Nadu, India

A Real Time Algorithm for Change Detection with the Aid of Multi-Resolution Wavelet Analysis

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ABSTRACT: The objective of this paper is to develop a procedure for change detection which is less sensitive to problems caused by misregistration, atmospheric effects and variations in vegetation phenology. If accurate registration between images is not achieved, spurious differences will be detected merely because the land surface properties at wrong locations are evaluated instead of real changes at the same location between one time and another. This project uses satellite images with a spatial resolution of 30 meters. Change Detection Algorithm named Wavechange is used to determine the changes that occurred in Madurai between the years 1996 to 2004. The procedure is based on redundant wavelet transform. Wavelet correlation is explored by taking point wise products of adjacent scales in order to enhance coefficients due to changes and smooth out noises. Local maxima are detected on the product spaces at varying spatial resolutions. The results showed that the method is not sensitive to geometric and radiometric misregistrations because of the multiresolution approach to feature extraction. The results are simulated using MATLAB.(Version 7).

KEYWORDS: Remote Sensing, Change Detection, Wavelet Product Spaces, Change Map.

I. INTRODUCTION

Wave change is an algorithm for reducing the noise in difference image produced by any of the traditional radiometric change detection methods. (eg. Differencing, rationing, principal component analysis, change vector analysis etc,.) Difference images produced by the methods listed above were reviewed by Singh [1]. They normally generate noisy outputs mainly due to the effects of misregistration, atmospheric conditions and phonological state of vegetation. These effects demand careful evaluation of the output difference images, which is prohibitive when large areas are to be evaluated. The limitation is further complicated when highly fragmented landscapes are under consideration.

While performing change analysis with remote sensing we normally compare image snapshots acquired at intervals of time. This analysis inherits characteristics of single-date image processing and rise new ones related to the integration of multitemporal datasets. There are a number of challenges to be overcome for an effective analysis of time-series from Earth observation: (1) errors result from the process of geometric transformation during image matching, (2) the spatial resolution of sensors, the degree of landscape fragmentation, and the nature of boundaries between objects pose limitations to the size of changes to be observed, (3) temporal scales in which changes occur vary according to the processes under investigation, (4) atmospheric conditions by the time of image acquisition might generate differences that can be misinterpreted as land cover change, (5) the radiometric response of objects on the Earth's surface might not differ in the spectral region covered by the sensor, (6) the phonological stage of vegetation vary along the year leading to differences that are not due to changes in land cover, and (7) some changes are gradual and their detection is difficult. The aim of the study was to develop a procedure for change detection which is less sensitive to some of the limitations described above. Specifically, the problems caused by misregistration are tackled.

II. METHODOLOGY

In the framework of this proposed work, the change detection algorithm is designed for reducing the noise in the difference image of Madurai images of 1996 and 2004. This algorithm is based on the wavelet analysis. The steps on this algorithm are explained as below.

A. Multiresolution Wavelet Analysis

Meyer [2] introduces multiresolution using a metaphor: "From a subtle and complicated image, one may extract a schematic version being a sketchy approximation resembling the pictures one can find in cartoons." Then, a set of better sketchy approximations of the original image resembles a multiresolution representation. The goal in multiresolution analysis is the decomposition of the whole space of functions into subspaces V_j. Functions are projected at each step of analysis onto finer subspaces such that each subspace V_j is contained in the previous subspace V_{j-1}. A function $f(t)$ in the whole space has a projection in each subspace. These projections represent the information contained in $f(t)$ in an increasing fashion, such that $f_j(t)$ (i.e., the projection of $f(t)$ in V_j approaches $f(t)$ for decreasing *j*. Besides the hierarchic and complete scale of (sub-) spaces other requirements are crucial to the notion of multiresolution. The dilation requirement states that if a function $\Phi(t)$ is in V_j, then $\Phi(2t)$ is in V_{j-1}. The translation requirement states that if $\Phi(t)$ is in V_0, then so are all its translates $\Phi(t-k)$. The final requirement states that the function $\Phi(t)$ with translate $\Phi(t-1)$ must form a stable basis for V_0, i.e. a Riesz basis: a complete set of linearly independent testing functions, say $\Phi_i(t)$, that represents in a unique way every function in V_0 as $\sum a_i \Phi_i(t)$, with $\sum |a_i|$ being finite. Then considering dilation by *j* and translations by *k*, we have:

$$F_j(t) = \sum_k a_{jk} \Phi_{jk}(t)$$

Representing the projection of $f(t)$ in V_j.

The associated error space when moving from V_j to V_{j+1} is the wavelet spaces W_{j+1}. The wavelet space, which is seemingly generated by dilations and translations of a single function, contains the "difference in information" $\Delta f_{j+1} = f_j(t) - f_{j+1}(t)$, which is the "detail" at level *j+1*. Each function in V_j is then the sum of two parts, $f_{j+1}(t)$ in V_{j+1} and $\Delta f_{j+1}(t)$ in $W_{j+1}(t)$. Considering the subspaces they lie in, we have:

$$V_{j+1} + W_{j+1} = V_j$$

And we have the complete information of $f(t)$ is,

$$f(t) = \sum_k a_{jk} \Phi_{jk}(t) + \sum_{j=1}^{J} \sum_k d_{jk} W_{jk}(t)$$

the coefficients a_{jk}, representing the projection $f_j(t)$ on $V_j(t)$ are obtained with inner product,

$$a_{jk} = \langle f(t), \Phi_{jk}(t) \rangle$$

whereas, the coefficients d_{jk}, representing the projections $\Delta f_j(t)$ on W_j are obtained with the inner product,

$$d_{jk} = \langle f(t), W_{jk}(t) \rangle$$

B. Redundant Wavelet Transform

Redundant wavelet transforms are also known as Nonorthogonal, over complete, undecimated or translation invariant wavelet transforms. They have superior de-noising capabilities when compared to move traditional transforms such as the (bi)orthogonal ones, Because of their translation invariance and the absence of visual artifacts in the de-noised outputs [3]. The following redundant transform was introduced by Holschneider et al [4] and will be used. The algorithm will be described considering that input signals are a function of one variable $f(t)$. Extensions to $f(T)$, with $T = (t_1, t_2, ... t_n)$, are obtained by separable filtering: Let $f(t) = a_0$, and *l* be symmetric. Then, the projection onto V_j are,

$$a_{j,k} = \sum_{l} h(l) a_{j-1,k+2^{j-1}l}$$

Whereas, the projections onto W_j are,

$$d_{j,k} = a_{j-1,k} - a_{j,k}$$

The reconstruction formula is,

$$a_{0,k} = a_{j,k} + \sum_{j=1}^{J} d_{j,k}$$

The result of a 2D algorithm is obtained with a separable wavelet and computed row by row and column by column via convolution with a B3(Cubic) Spline wavelet, which leads to the filter h=(1/16, ¼, 3/8, ¼, 1/16).

C. Thresholding function

The suitable threshold function applied to the wavelet coefficients. The thresholding is used for the De-noising purpose. Before multiscale product calibration, the wavelet coefficients were thresholded. There are two types of thresholding techniques. They are the soft thresholding and hard thresholding. In this study, the soft threshold [6] is used.

$$\delta_T(t) = \begin{cases} 0 \\ sign[a_i](|a_i| - T) \end{cases}$$

Where,

$\delta_T(t)$ - Soft thresholded image

T - Threshold

a_i – Transformed Matrix

$$T = \hat{\sigma}_{<mad>} \sqrt{\ln(N)}$$

The threshold value T may vary from scale to scale resulting in a locally adaptive function evaluation. There are different ways of selecting a suitable threshold value 'T' to be used in the thresholding function. For the present study, the threshold value is statistically calculated based on the median absolute deviation [7]. A suitable estimator for the standard deviation is,

$$\hat{\sigma}_{<mad>} = \frac{median\{|W_1|, |W_2|, \ldots |W_{N/2-1}|\}}{0.6745}$$

Where,

N - Number of coefficients

W_i - Wavelet coefficients

$\hat{\sigma}_{<mad>}$ - Median

D. Wavelet Spatial Correlation

Pioneering work on calculating spatial correlation by mutiscale wavelet products was carried out by Rosenfeld et al [5]. The idea is that, the sharp edges and significant singularities show large wavelet coefficients over many wavelet scales, whereas coefficients due to noise tend to smooth out very rapidly [3]. Hence, multiplying the adjacent wavelet scales would enhance edges while diminishing noise.

Wavelet correlation $P_J(t)$ is computed by the point wise product of wavelet coefficient at adjacent scales.

$$P_J(t) = \prod_{j=1}^{J} W_j(t)$$

Where,

$P_J(t)$ - Wavelet Correlation

$W_j(t)$ - Adjacent Wavelet Scales

It is sufficient to explore spatial correlation by employing two adjacent scales. Multiscale products are calculated using only intermediate wavelet scales to filter out spurious effects of misregistration and to reduce the search effort.

III. EXPERIMENTAL RESULTS and DISCUSSION

A. Study Area

The selected area for this research is the Madurai City, Tamilnadu. Madurai is the second largest city in Tamilnadu, after Chennai and is one of the oldest cities in India, over 2,500 years old. Madurai has been identified as the next IT destination behind Chennai and Coimbatore and symbolizes a typical Tier II city where there is an urgent need for novel urban planning methods. Madurai is situated between the longitude 78^0 04' 47" E to 78^0 11' 23" E and the latitude 9^0 50' 59" N to 9^0 57' 36" N. The topography of Madurai is approximately 101 meters above the sea level. This city is surrounded by hundreds of villages from which people area migrating for employment. Madurai city had a population of about 9 lakhs in 1991 and now has a population of about 14 lakhs.

B. Data Used

Two kinds of satellite data with different resolution and acquisition dates (LISS II and LISS III) were used in this research. The details of the sensor used, resolution are tabulated as follows.

TABLE 1 INPUT DATA DETAILS

	Date of Acquisition	Satellite / Sensor	Resolution
Image 1	4th March, 1996	IRS 1B / LISS II	36.25 Meter
Image 2	19th March, 2004	IRS P6 / LISS III	23.50 Meter

The Linear Imaging Self Scanner II (LISS II) has spatial resolution of 36.25m, multi-spectral channels in the Visible and Near Infra-red Wavelength. Observation Spectral Characteristics of LISS II are,

Band 1 0.45 ~ 0.52 µm

Band 2 0.52 ~ 0.59 µm
Band 3 0.62 ~ 0.68 µm
Band 4 0.77 ~ 0.86 µm

The Linear Imaging Self Scanner III (LISS III) has spatial resolution of 23.5m, multi-spectral channels in the Visible and Near Infra-red Wavelength. Observation Spectral Characteristics of LISS III are,

Band 2 0.52 ~ 0.59 µm
Band 3 0.62 ~ 0.68 µm
Band 4 0.77 ~ 0.86 µm
Band 5 1.55 ~ 1.70 µm

The data applied in this research were the last three bands (B2, B3 & B4) of IRS 1B - LISS II data with 36.25 meter resolution acquired on date of 4^{th} March 1996, and first three bands of IRS P6 – LISS III (B2, B3 & B4) with 23.5 meter resolution acquired on date of 19^{th} March 2004. Survey of India topographic sheets 58 K/1 in 1: 50, 000 scale and four 58 K/1 SW, SE, NW, NE in 1:25,000 scale were used as reference data for the verification and analysis.

For this paper, the image of Madurai taken at different durations says 1996 and 2004. The sizes of the images are 419x502. The simulation results suggest that, the small area changes and geometric misregistration are captured by wavelet products, whereas, overall changes such as variation due to phenology and atmospheric conditions are captured at the smoothed representation of the original difference image.

C. Experimental Results

The experimental results of Wavechange algorithm for change detection based on wavelet product scales is simulated by MATLAB 7.0. This experimental results says that, the small area changes and Geometric Misregistration are captured in the fine wavelet scales, whereas, the overall changes, such as variations due to phenology and atmospheric conditions are captured at the smoothed representation of the original difference image. Thus, the multiscale products are calculated using only intermediate wavelet scales to filter out spurious effects of Misregistration and to reduce the search effort. The overall difference between the images are captured by the smoothed approximation of the wavelet transform (i.e., the projection $f_j(t)$ on V_j) and not used to generate the multiscale product space.

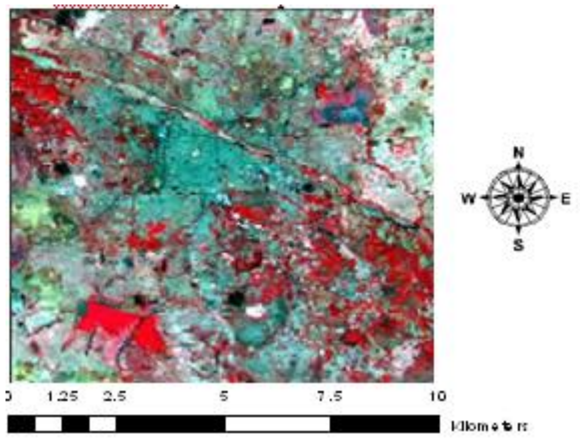

Fig.1: Madurai Images from 1996

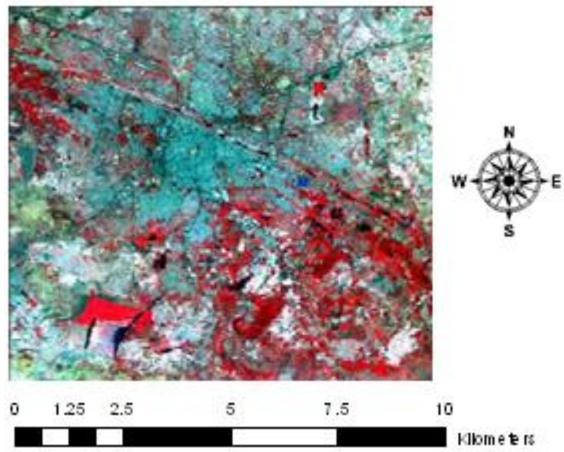

Fig.2: Madurai Images from 2004

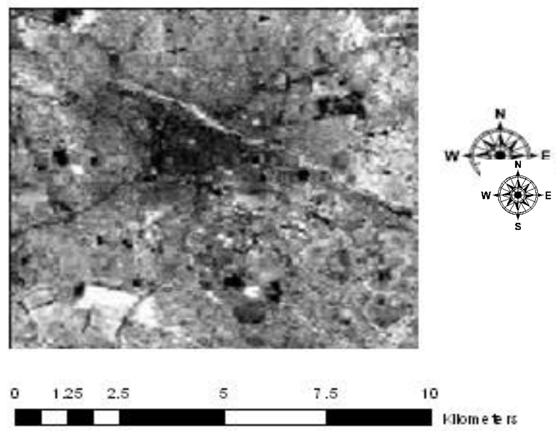

Fig.3: Madurai Image from 1996 but misregistred (Red Band)

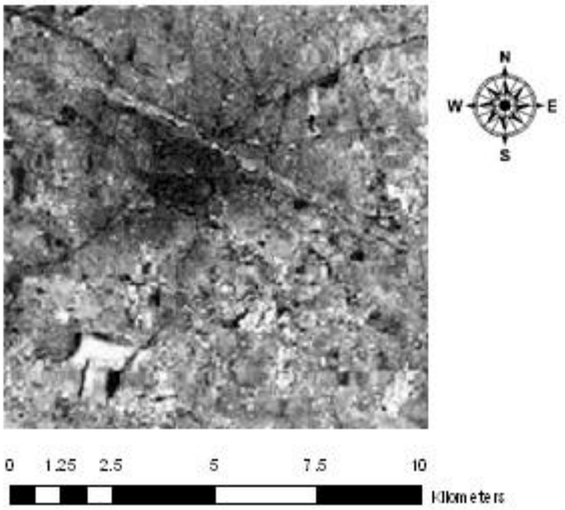

Fig.4: Madurai Image from 2004 (Red Band)

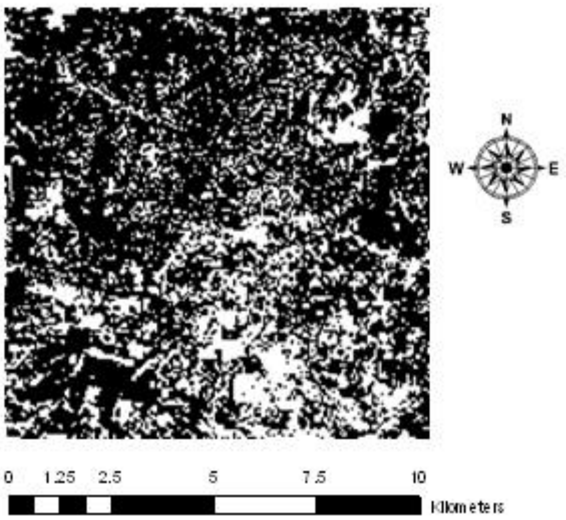

Fig.5: Thresholded Difference Image without misregistration

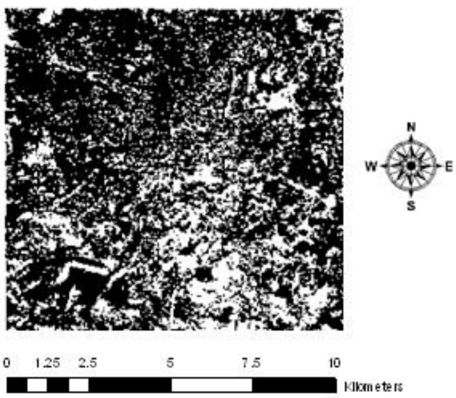

Fig.6: Thresholded Difference Image with Misregistration

TABLE 2: COMPARISON TABLE for CHANGE DETECTION ACCURACY with RESPECT to REGISTRATION

EFFECT OF CHANGE DETECTION WITH RESPECT TO REGISTRATION	KAPPA COEFFICIENT
WITHOUT MISREGISTRATION	0.5805
WITH MISREGISTRATION	0.5079

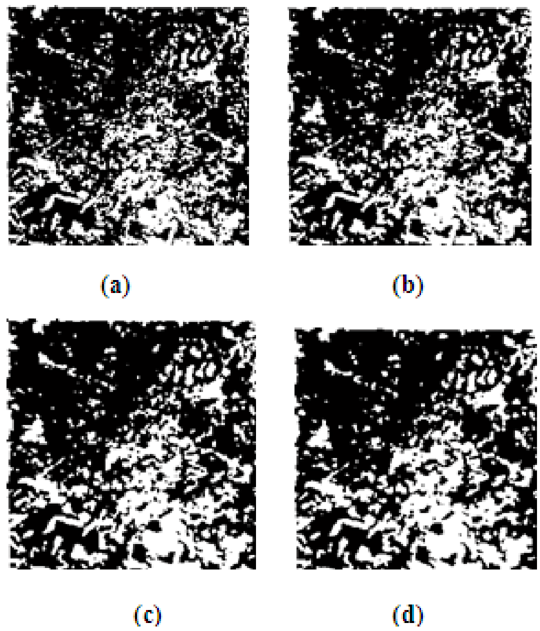

Fig.7: product of wavelet spaces 1x2(a), 2x3 (b), 3x4 (c), 4x5 (d)

WAVELET PRODUCT SPACES	KAPPA COEFFICIENT
PRODUCT OF WAVELET SCALES 1x2	0.5787
PRODUCT OF WAVELET SCALES 2x3	0.5625
PRODUCT OF WAVELET SCALES 3x4	0.5594
PRODUCT OF WAVELET SCALES 4x5	0.5594

The maxima points appearing in the wavelet product scales are due to the real changes, whereas, the relatively high values in the difference image due to the atmospheric differences and misregistrations are bypassed. Thus, the property of the multiscale product transform is illustrated in this experimental result and by the accuracy table.

IV. CONCLUSION

Digital change detection techniques aim to detect changes in images over time. These differences may be due to an actual change in land cover or differences in illumination, atmospheric conditions, Image misregistration, sensor calibration or ground moisture conditions. The calibration of data or standardization between dates may be necessary. In this project, a framework for digital change detection using wavelet product space has been developed and evaluated on Madurai city images. The approach is relatively simple and provides further refinements to procedures such as image differencing or rationing. The method is less sensitive to geometric and radiometric misregistrations because of multiresolution approach to feature extraction.

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