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Use of Radar Remote Sensing for Land Use Dynamic Monitoring in South West Coast of Caspian Sea

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ABSTRACT

The southern coast of the Caspian Sea is characterized by high humidity with wide clouds and fog covers. Because of this feature in the region, it is difficult to acquire satisfactory optic image from satellite image for interpretation. This has influence on land use dynamic monitoring around the southern cost of the Caspian Sea. Radar remote sensing has many advantages on the application of land use survey in the study area because of less effect of weather in comparison with the Landsat TM data. In the study a developed image enhancement technique on the basis of Kalman filtering technique was proposed. Texture analysis of Radar SAR image was investigated. The method used in the current project for Land use/cover changes detection from 2005 to 2007 was to fuse images of different sources such as TM and SAR and then integrate the fused images of different times in such that the changes of these images can be highlighted. Radar SAR data and TM Images captured in 2005 and 2007 were used for this purpose. The techniques that are applicable to both the Radar data and to TM data as well as to the accuracy of results obtained for land use monitoring have been systematically compared. The results of the study verify the efficiency of the proposed Kalaman filtering technique for dynamic land use monitoring in particular study area.

Keywords: Remote Sensing, Radar SAR, Filtering, Land use, Landsat TM

1. Introduction

Land use and land cover change has become a central component in current strategies for managing natural resources and monitoring environmental changes (Opeyemi, 2006). In order to use land optimally, it is necessary to have information on the existing land use/cover and the capability to monitor the dynamic changes of land use/cover resulting from the newer demands of an increasing population and the change of lifestyle of that population (Joseph, 2005).Radar remote sensing can be utilized in the civilian field for disaster surveillance of: earthquakes, floods, wild fires, mud/rock flows, and other naturally occurring disasters (Wood, 2009). It can be used to monitor and survey ocean resources, the ocean environment and seaport activity. Radar SAR data can be used for monitoring and assessing environmental change and pollution detection; it can obtain the change information over time for marsh change, urban extension, and terrain change; it can update the basic geographic database (Merril and Jiajun, 1998). In the military field, SAR can be used as continuous reconnaissance tool for the battlefield arena and for continuous detection of key monitoring targets (Quegan *et. al.,* 2000). Using a Radar system to study the earth (or another planet) has several advantages over passive sensors. The wavelength of the Radar signals can detect features through cloud layers, and as is an active system which can operate day or night (Mouginis, 2007). Several image classification techniques from Radar SAR data can be found in the literature, very few studies (Wu and Liu, 2001; Karvonen, 2003; Tupin and Roux, 2003; Clausi and Yue, 2004; Maillard, Clausi and Deng, 2005; Gamba, Acqua and Lisini, 2006; Stoica, Xu, and Roberts, 2007) have used/compared Radar SAR data for feature detection, extraction and classification. The main objective of the present study: to develop a specific Kalman filtering technique for high resolution extraction and precise filtering for monitoring land use/ cover change detection in regions which have high humid along with stratoform cloud layers. The southern coast of Caspian Sea provides the test conditions for this case study. Multi-parameter Radar remote sensing data were applied to measure the changes of land uses. Combining visual interpretation and computer automated classification, potential targets with land use changing can be evaluated on the basis of relative change of image patterns by comparing the field survey results with the results obtained from processing Radar SAR remote sensing data and other optic remote sensing data with various parameters and for two different time periods.

2. Materials and Method

2.1. Study area

According to the main objective of the study which was to develop a filtering technique for improving land use/ cover monitoring in high humid and cloudy regions, Guilan Province which is one of the northern provinces of Iran with an area of 14711 square meters was selected. The area under study lies between 48° 53´ and 50° 34´ North latitudes and 36° 34´and 38° 27´ East longitude. Its length is 235 kilometers from the northwest toward the southeast and its width varies from 25 to 105 kilometers.

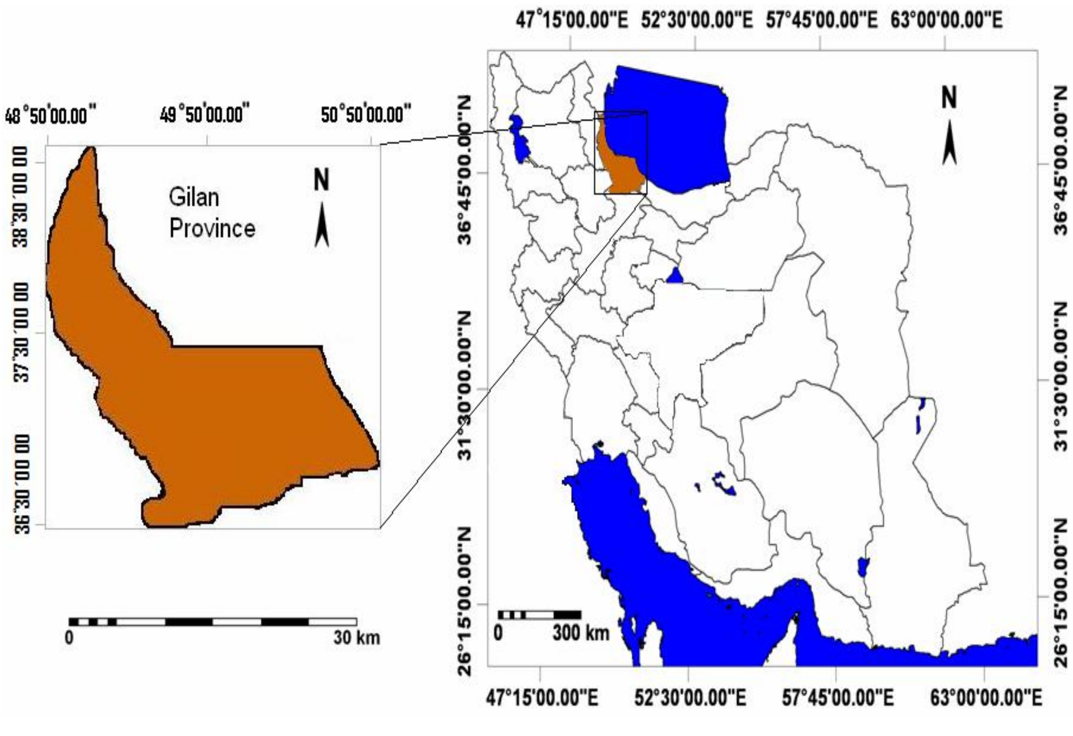

Figure 1: Location map of study area

The study area is in the vicinity of the Alborz Mountain. The northern border of the Guilan Province is marked by the Caspian Sea and the borders of other independent countries of Middle Asia. The other borders are marked by Ardebil Province on the west, the Zanjan and Ghazvin Provinces on the south, and the Mazandaran Province on the east.

Guilan Province has 16 cities, 48 towns, 43 districts, 109 rural districts and 2892 villages (2690 villages with inhabitants and 202 villages without inhabitants). Population of Guilan Province is 2,458,902 individuals, from which 1,250,791 live in cities and 1,208,111 are villagers. In regard to relative population density, Guilan Province is the second in Iran after Tehran Province. Density of population in Guilan Province is 167.1 people per each square kilometer. Numerous factors such as favorable climate, moist and fertile soil, existence of permanent current water networks, abundant and various agricultural facilities and well extended connection roads cause the intense density of population in the province.

Climate of Guilan Province is temperate due to its location between the Alborz Mountains and the Caspian Sea. With respect to Guilan Province's adjacency to the Caspian Sea, the climate is highly humid and precipitation is not well distributed in all parts of the province which make it difficult for passive sensor to take clean images. . The greatest rainfall occurs on the plain of Bandar Anzali City with average annual of 2000 millimeters. The least amount of rainfall in the province occurs along the areas of Roudbar, Loshan, and Manjil with the average annual amount of 200 millimeters. The days with freezing weather is limited and dispersed and the temperature is seldom less than –1 degree centigrade. Astara is the coldest and Bandar Anzali is the warmest among the province cities. Lahijan has the most favorable weather than any other point in the province, as it has the warmest winters and coolest summers.

2.2. Data sources

Radar SAR data and TM Images (spatial resolution 30m) captured in 2005 and 2007 were used in the study. In order to compare the results, two sets of SAR images were taken of the same location and at different times. The first set of images includes SAR images 2007.5.14, and 2005.7.11 and the second set taken were of 2007.5.13, and 2005.11.23. Rectification and registration of Radar SAR data were based on control points collected from topographic maps. The same processes and methods were applied to these two image sets.

2.3. Enhancement of Radar SAR images

In Radar SAR image processing, it often needs to smooth out noises while retaining edges or shape features in the image. The filtered image is therefore easier for visual interpretation. The method for algorithm of image enhancement of the SAR imagery in the study aggregates from , Kalman dynamic filtering technique which is one of the most efficient techniques to provide optimal liner estimation of the non-stationary random characteristics of SAR imagery.

Here, we consider the following assumed discrete model for the SAR observation process

$$\zeta_v = H_v\lambda_v + U_v + n_{0v} \text{ and } \lambda_v = \beta_{v\_1}\lambda_{v\_1} + n_{\lambda v} \quad (1)$$

Where H_v is SAR observation data represents the measurement coupling operator, u_v is a dynamic control function, β_v is a transition function, The noise n_{0v} has a complex Gaussian noise with a zero mean value and variance D_{0v}, while $n_{\lambda v}$ is referred to as the system dynamic model zero-mean white Gaussian noise. The later is characterized by the variance $D_{\lambda v}$ and Δ ($t_v - t_{v-1}$) represents a sample step in discrete time.

Then for improvement of precise filtering of desired characteristics λ_v in Kalman technique the bellow equations are applied:

$$\hat{\lambda}_v = \beta_{v-1}\hat{\lambda}_{v-1} + k_v\left(\zeta_v - u_v - H_v\beta_{v-1}\hat{\lambda}_{v-1}\right) \quad ; \tag{2}$$

$$\frac{1}{R_v} = \frac{1}{\beta_{v-1}^2 R_{v-1} + D_{\lambda v}} + \frac{H_v^2}{D_{0v}} \quad ; \tag{3}$$

$$K_v = H_v . \frac{R_v}{D_{0v}}$$

The technique of enhancement filtering for dynamic monitoring of land use/cover is shown as below figure:

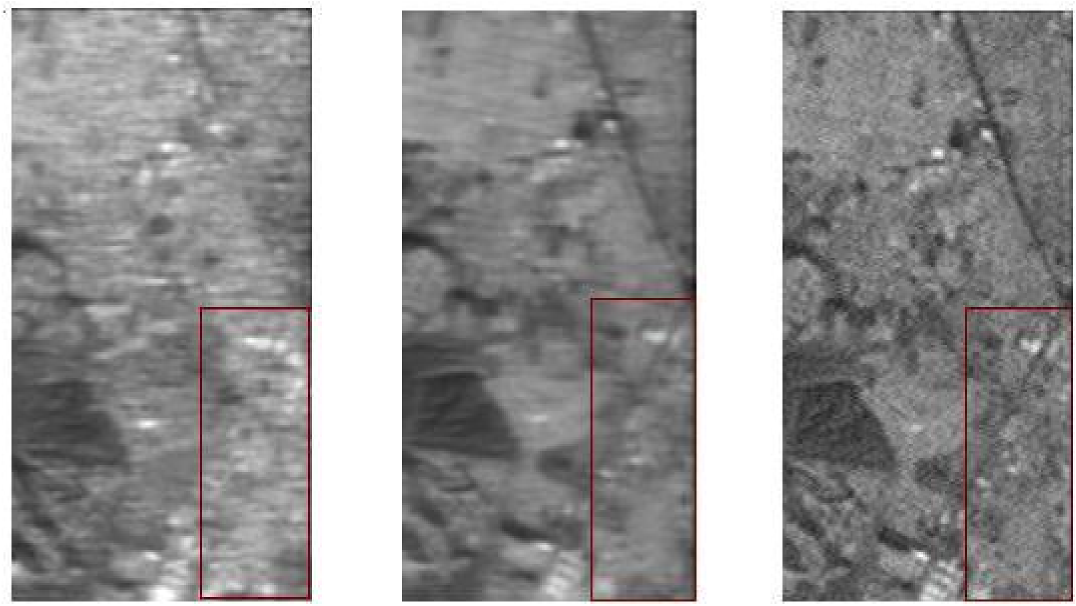

Figure 2: The compression of detection on SAR Images on basis of developed Kalman technique

The filtered SAR images of 2005 and 2007 have been further fused with Landsat TM images. This technique has been shown to be effective for distinguishing land use patterns.

2.4. Texture Analysis of Radar SAR image for land cover classification of optical image

The hypothesis is that adding texture to a classification will increase land cover map accuracy and is consistent with the use of texture as an element of photo interpretation in high density vegetation areas (Leckie *et al.,* 1995). Image texture is a quantification of the spatial variation of image tone values that are related to changes in the spatial distribution of land cover, both in the vertical and horizontal dimensions (Franklin *et al*., 2000). Image texture is a complex concept and application. Simple texture measures may be derived by comparing the values of the digital numbers within a window, or in derivatives of a matrix representing the grey level co-occurrence within the window (Haralick 1979, Oja and Valkealahti 1996).

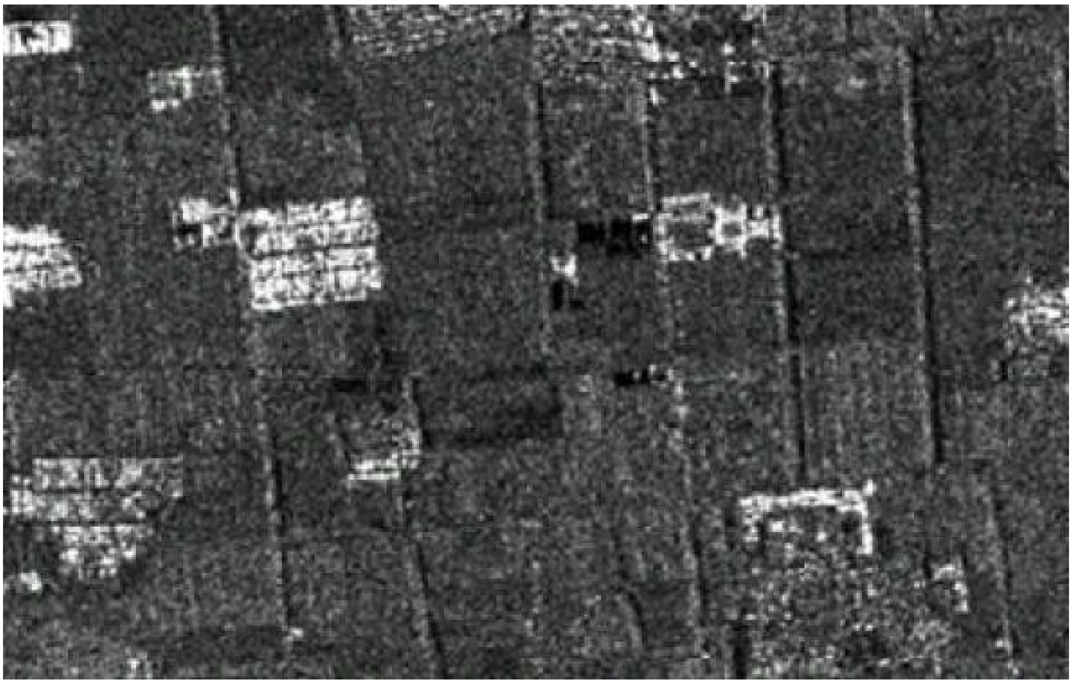

Figure 3: Sample of enhanced Radar SAR image by edge enhancement filtering

Two co-occurrence texture derivatives described by Franklin and Peddle (1987) were applied to the infrared channel wavelength (approximately 740 ± 760nm) to characterize the texture of the vegetation for each plot. Only simple texture measures were derived based on preliminary interpretations of image displays (Franklin and Peddle 1990) to illustrate their use and the degree of improvement possible in plot classification. More complex multidimensional texture measures are possible, and subsequent study may attempt to optimize the texture measures. The size of the window over which texture measures are derived may be altered or adapted to better represent the characteristics of the local area (Haralick 1986, Marceau *et al.* 1990, Ryherd and Woodcock 1997). Large windows (e.g., 9×9 compared to 3×3) can provide better estimates of distributions and decrease the random error, but may encompass more than one stand type that can introduce systematic error. An increased ability to estimate forest stand parameters such as stand density and volume have been reported after customized windows sizes were used rather than fixed arbitrary windows (Franklin and McDermid 1993, Wulder *et al.* 1998). These are data-driven *geographic windows*, rather than arbitrary, fixed *geometric windows* (Franklin *et al.* 1996). An inter-pixel sampling distance of one and a zero degree angle were utilized on 8-bit linearly transformed 16-bit data to calculate the texture derivatives from the spatial co-occurrence matrix. Texture measures homogeneity was used in this study (PCI Inc. 1994):

$$\text{Homogeneity} = \sum_{j-1}^{n} \sum_{i-1}^{m} \frac{P(i,j)}{(1+[R(i)-C(j)]^2)} \qquad (4)$$

where $P(i,j)$ is the spatial co-occurrence matrix element, $R(i\ )$ is the grey level value for a row, and $C(\ j\ )$ is the grey level value for a column.

2.5. Radar Data Fusion

Data fusion normally refers to the process to integrate and view several types of data from different sources. Using PCI, a new color image can be generated by fusing the color component of one input image with the intensity component of another input image (Joseph, 2005). Image fuse has been commonly applied for synthesis multiple image for interpretation. There have been developed a numerous synthetic methods for remote sensing data fusing such as: Lab transfer, IHS transform, Brovey transform, and wavelet transform (Qinghua *et al*, 2001).

These methods work for different purposes on different application conditions (Chuvico and Congalton, 1996). In this study, HIS and Brovey transform methods were applied. The advantage of encoding of HIS is that it can separate the colors (H), intensity (I), and amount of saturation (S). The Brovey transform is a kind of modified RGB transform that involves a normalization of RGB bands by the sum of all bands (R+G+B) and then multiplied by the intensity layer (Lillesand and Kiefer, 2002). It can be used to integrate different data for example, taking TM as RGB bands and the enhanced SAR data as the intensity layer.

This is helpful for differentiating patterns reflecting mountains, water, plants, construction areas, and green areas. Two combinations of TM bands 7, 4, 3 and SAR data were implemented in HIS and Brovey transforms in the selected area to indicate the result

Figure 4: Examples of HIS fused and SAR images (on the left) and Brovery fused TM and SAR images (on the right)

Finally, an identification of land patches can be made both based on the change of spectrum and textures of the images in different years as it is shown in Figure 5.

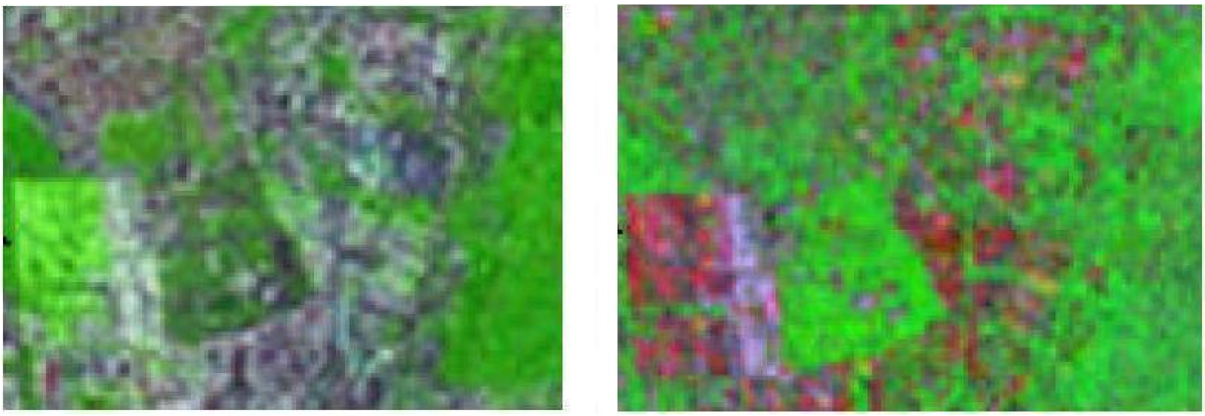

Figure 5: Example of HIS fused TM and SAR images RGB- TM bands 7 4 3 and Intensity-SAR shown land patches(low green), and fused different time SAR images R 00/06, G 00/05, B 97/11- SAR shown land patches(red) on the right

4. Conclusion

It is indicated that, a new developed technique of Kalman filtering by SAR imagery used in the study improves dynamic monitoring of land use and it has been demonstrated that applying proper image processing and analysis techniques to Radar SAR data alone or with TM images can effectively monitor land use changes. Removing the influences of noise and edge effects of SAR data by image filtering is essential for detection of patches with true land use changes. Field validation of a significant number of sites is always necessary for evaluating the classification results to ensure the results meet the required standards.

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