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Full Length Research Paper

Object recognitions in RADARSAT-1 SAR data using fuzzy classification

Maged Marghany[1]*, Mazlan Hashim[1] and Farideh Moradi[2]

[1]Institute of Geospatial Science and Technology (INSTeG), Universiti Teknologi Malaysia, 81310 UTM, Skudai, Johore Bahru, Malaysia.
[2]Faculty of Physics, Science and Research Branch, Islamic Azad University, Tehran, Iran.

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This study is aimed to utilize fuzzy classification for different object detections that is urban, infrastructure and coastal water in RADARSAT-1 SAR S2 mode data. Prior to fuzzy classification, Lee algorithm with kernel window sizes of 7 × 7 pixels and lines is implemented to S2 mode data. Indeed, speckle reduction is performed using Lee algorithm. The results show that Lee algorithm is able to provide excellent information about linear infrastructure and urban features in SAR data. Further, fuzzy classification can discriminate between urban zone and coastal waters. In conclusion, the integration between Lee algorithm and fuzzy classification can be used for different object recognitions in S2 mode data.

Key words: RADARSAT-1 SAR, fuzzy classification, Lee algorithm, object recognitions.

INTRODUCTION

Automatic object detection and recognition in synthetic aperture radar (SAR) images is an area of ongoing research by all branches of the military and large research institutions. Nevertheless, speckles has posed great difficulties in inverting SAR images for both object automatic detection and recognition. According to Marghany and Mazlan (2010a) speckle is a result of coherent interference effects among scatterers that are randomly distributed within each resolution cell. The speckle size is a function of the spatial resolution, which induces errors in object feature signature detection. In order to reduce these speckle effects, appropriate filters, for example, Lee, Gaussian, etc. (Lee et al., 2002), can be used in the pre-processing stage. The effectiveness of these speckle-reducing filters, however is influenced by local factors and application. In fact, all speckles in SAR images are related to local changes in object surface roughness. In this context, Marghany et al. (2010) agreed with Yu and Scott (2002) and Hondt et al., (2006) that there are several limitations of the speckle filtering approach. They reported that the size and shape of the filter window can affect the accuracy level of despeckle filters (Maged, 2001a). For instance, a large window size should form a blurred output image, while a small window will decrease the smoothing capability of the filter and will leave speckle. In spite of despeckle filters performing edge enhancement, speckle in the neighborhood of an edge (or near a point feature with high contrast) will remain after filtering (Nezry et al., 1993; Yu and Scott, 2002; Marghany and Mazlan, 2010b). Furthermore, the thresholds used in the enhanced filters, although motivated by statistical arguments, are ad hoc improvements that only demonstrate the insufficiency of the window-based approaches (Marghany and Mazlan, 2010a).

In recent years, satellite image classification based on fuzzy set theory have received much attention. Fuzzy classification is the process of grouping elements into a fuzzy set (Zadeh, 1965) whose membership function is defined by the truth value of a fuzzy propositional function. It has been discussed for example by Zimmermann (2000) and Meier et al. (2008). According to Zadeh (1984), Zimmermann (2000) and Meier et al., (2008), a fuzzy class is defined as a fuzzy set of individuals satisfying a fuzzy classification predicate which is a fuzzy propositional function. The domain of the fuzzy class operator is the set of variables V and the set of fuzzy propositional functions and the range is the fuzzy

*Corresponding author. E-mail: magedupm@hotmail.com.

power set (the set of fuzzy subsets) of this universe. Further, the degree of membership of an individual in the fuzzy class is defined by the truth value of the corresponding fuzzy predicate. Intuitively, a class is a set that is defined by a certain property and all objects having that property are elements of that class. The process of classification evaluates for a given set of objects whether they fulfill the classification property and consequentially are a member of the corresponding class. However, this intuitive concept has some logical subtleties that need clarification (Zimmermann, 2000).

Consequently, the main objective of this work is to utilize fuzzy algorithm and adaptive Lee algorithm for different object recognitions such as urban, infrastructure and coastal water in RADARSAT-1 SAR S2 mode data.

DATA AND METHODOLOGY

Data set

The SAR data acquired in this study are from the RADARSAT-1 Standard beam mode (S2) image which are C-band and have a lower signal-to noise ratio due to their HH polarization with wavelength of 5.6 cm and frequency of 5.3 GHz. RADARSAT-1 Standard beam mode (S2) data have 3.1 looks and cover incidence angle of 23.7° and 31.0° (Maged et al., 2009a, b). Indeed, spatial averaging of (4-look) SAR data reduces signal level fluctuation due to speckle to about 5% which equivalent to 0.2 dB. Therefore, a calibration accuracy of 0.2 dB appears an appropriate task for slick detection in RADARSAT-1 data. In addition, standard beam mode (S2) cover the swath width of 100 km, respectively.

Remove speckle noise using adaptive filters

The appearance of speckle noise is inherent to all coherent imaging systems such as synthetic aperture radar (SAR). Speckle arises from random interference of all backscatter signals within one imaging resolution cell. The maximum speckle effect occurs in totally unstructured areas and is referred to as fully developed speckle (Lee, 1981; Marghany and Mazlan, 2010a). It is important to address speckle noise before any other processing. For this study we used from Lee filter prior to a fuzzy classification to getting the best result. Following Marghany and Mazlan (2010a), Lee algorithm is implemented to SAR data by sliding rectangular window width and odd length. The windows size is selected in the two dimensions over the input images. At each window position, the mean and variance of the images intensity are estimated. Following Marghany and Mazlan (2010c), a combination of additive and multiplicative noise (speckle) was used for noise reduction from the multi SAR images. According to Lee (1981), the Lee algorithm can be given by the following equation:

$$R = \bar{U}_{grey} + K(CP - \bar{U}_{multiplicative}(\bar{U}_{filter} - \bar{U}_{additive})) \tag{1}$$

Where,

$$K = \frac{(\bar{U}_{multiplicative} \times \mu_{filter})}{(\mu_{filter} \times \bar{U}^2_{multiplicative} + \bar{U}^2_{filter} \times \mu_{multiplicative} + \mu_{additive})} \tag{2}$$

The multiplicative noise variance is calculated from local statistics in the filter window from the given Equation 2:

$$\mu_{multiplicative} = \frac{\sigma^2}{\bar{\mu}^2_{filter}} \tag{3}$$

μ_{filter} is the variance in filter window. $\mu_{multiplicative}$ represents the multiplicative noise variance, $\mu_{additive}$ is the additive noise variance, $\bar{U}_{filter}$ is the mean grey level in the filter window, $\bar{U}_{multiplicative}$ is the mean multiplicative noise $\bar{U}_{additive}$ is the mean additive noise, CP is the central pixel in filter window and SD is the standard deviation of the noise in the filter window. The value of mean additive noise is usually 0. The value of mean multiplicative noise is usually 1. The application of the algorithm aforementioned assumption that the mean value of additive noise is usually 0 and mean value of multiplicative noise is usually 1.0 (Lee, 1981; Marghany and Mazlan, 2010c).

Sigma nought estimation σ^0

It was done after using Lee algorithm. Sigma nought is a measure of the mean backscatter of a radar signal from an area of 1 m^2 on the earth's surface, typically denoted in decibels (dB). Sigma nought describes the backscattering strength of a distributed target, rather than a discrete target. Sigma nought used to calibrate RADARSAT data to radar backscatter coefficient (σ^0). This function requires a DEM with the same spatial dimensions and pixel size as the input radar data. The DEM image is used to accurately calculate the incidence angle over the image. The radar backscatter coefficient values are output in decibels (dB) (Ulaby et al., 1982; Horritt et al., 2001). The radar backscattering coefficient σ^0 is related to the radar brightness β^0 as follows:

$$\sigma^0_j = \beta^0_j + 10 \log_{10}(\sin \theta_i) \tag{4}$$

Where θ_i is the incidence angle at the *j th* range pixel. This formula assumes that the earth is a smooth ellipsoid at sea level.

Feature extraction procedures using fuzzy classification approach

Here describes the procedures that have been used to extract landuse pattern from RADARSAT-1 SAR image. Generally supervised classification is more closely controlled than unsupervised classification. In this process, select pixels that represent patterns recognition. Knowledge of the data, the classes desired and the algorithm to be used is required before beginning selecting training samples. By identifying patterns in the imagery, it is possible to train the computer system to identify pixels with similar characteristics. By setting priorities to these classes, we can supervise the classification of pixels as they are assigned to a class value. If the classification is accurate, then each resulting class corresponds to a pattern originally identified. After training data and prepare signature file we used fuzzy classification (Figure 1) in order to acquire requested classes which includes: urban, water and vegetable zones. The last step in this phase used fuzzy convolution operation that creates a single classification band by calculating the total weighted inverse distance of all the classes in a window of pixels and assigning the center pixel the class with the

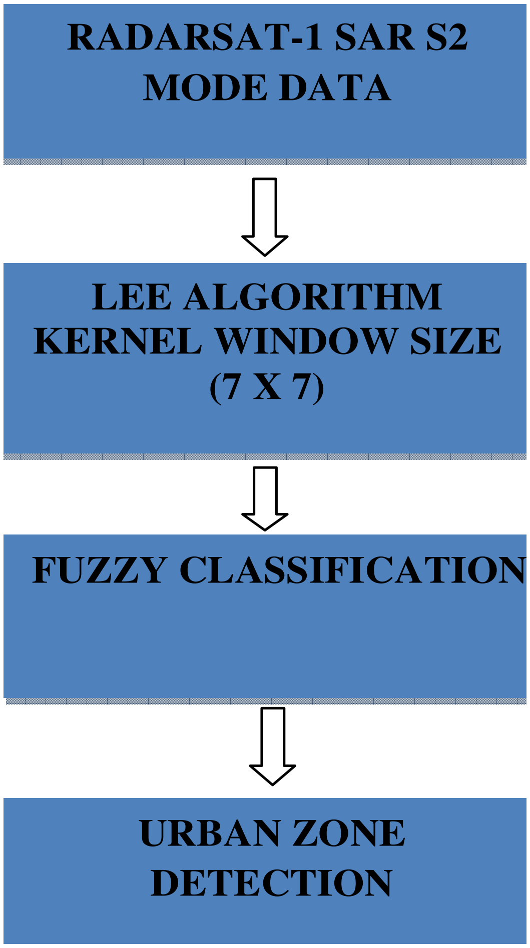

Figure 1. Block diagram of urban detection using fuzzy classification.

largest total inverse distance summed over the entire set of fuzzy classification bands (Mather, 1999).

Classes with a very small distance value remain unchanged while classes with higher distance values may change to a neighboring value if there is a sufficient number of neighboring pixels with class values and small corresponding distance values. The following equation is used in the calculation as the center pixel is assigned the class with the maximum *f (c)*:

$$f(c) = \sum_{i=0}^{z} \sum_{j=0}^{z} \sum_{s}^{n} \frac{w_{ij}}{d_{ijs[c]}} \quad (5)$$

where *i* is row index of window, *j* is column index of window, *s* is size of window (3, 5 or 7), *s* is layer index of fuzzy set, *n* is number of fuzzy layers used, *w* is weight table for window, c is class value, *d(c)* is distance file value for class *c* and *f(c)* is total weighted distance of window for class *c* (ERDAS, 1999).

RESULTS

Figure 2 shows the impact of Lee algorithm in RADARSAT-1 SAR data. Clearly, the reduction of speckle can be noticed in Figure 2b. In Figure 2b, the urban zone is shown as most brightness pixels as compared to the surrounding environments. Figures 3 and 4 shows the output classification map by using fuzzy classification algorithm. Classes with a very small distance value remain unchanged while classes with higher distance values may change to a neighboring value if there are a sufficient number of neighboring pixels with class values and small corresponding distance values (Figures 3 and 4). The backscatter of different objects such as urban and water areas is presented in Figure 5. The effect of physical properties of features may produce different changes in measure of backscatter in the SAR images. Comparison between spatial profile of backscatter between water and urban area in Figure 5 showed that water area has lower backscatter value of -50 dB as compared to urban zone that is -8 dB.

DISCUSSION

It is obvious that the clear appearance of the urban features in RADARSAT-1 SAR S2 beam mode. In fact, the Lee algorithm avoids a decreasing resolution by making a weighted combination of running average with the neighbor surrounding pixels (Figure 1b). This reduced the noise in the features' edge areas without sacrificing edge sharpness. This result confirms Marghany and Mazlan (2010a) study. Further, Lee algorithm has the effect of creating a context-based classification to reduce the speckle or "salt and pepper" in the classification map which is produced by fuzzy classification. The backscatter variations along the coastal waters and urban zones show different trend where amount of backscatter reduces in boundary between urban and water regions. Smooth water surface acts like a specular reflector (Ulby et al., 1982; Lillesand and Kiefer, 1999) and specular reflection of the incident energy (generally away from the sensor) causes just only a small amount of energy is returned to the radar. According to Lillesand and Kiefer (1999) and Horritt et al. (2001) smooth surfaces appearing as darker toned areas on an image and very low backscatter. While in urban area features which have two (or more) surfaces (usually smooth) at right angles to one another, may cause corner reflection to occur if the 'corner' faces the general direction of the radar antenna. However, this concept is not always true because of mix pixels in land or water areas that may create complex behavior of different backscatter. Further, the orientation of the surfaces at right angles causes most of the radar energy to be reflected directly back to the antenna due to the double bounce (or more) reflection.

Corner reflectors with complex angular shapes are common in urban environments (that is buildings and streets, bridges and other man-made structures). Naturally occurring corner reflectors may include severely folded rock and cliff faces or upright vegetation standing in water. In all cases, corner reflectors show up as very

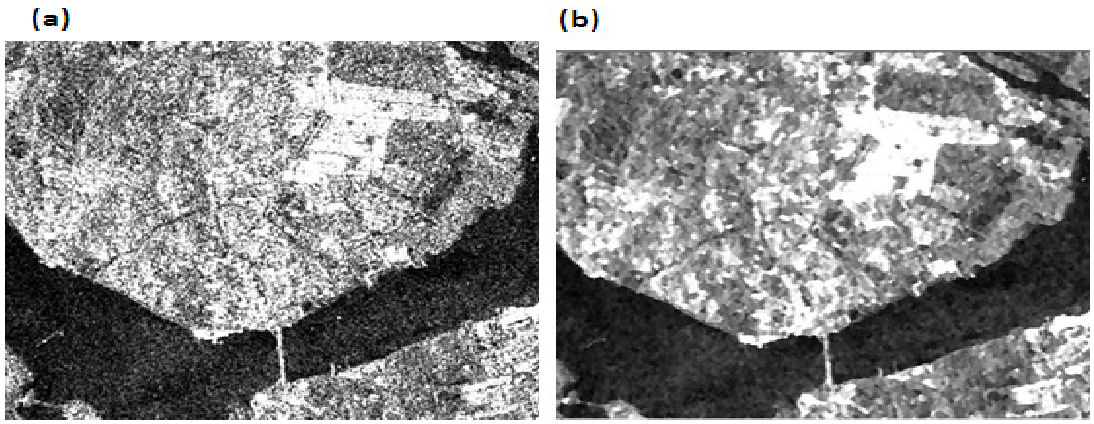

Figure 2. Spekles reduction in (a) raw RADARSAT-1 SAR image using (b) Lee filter.

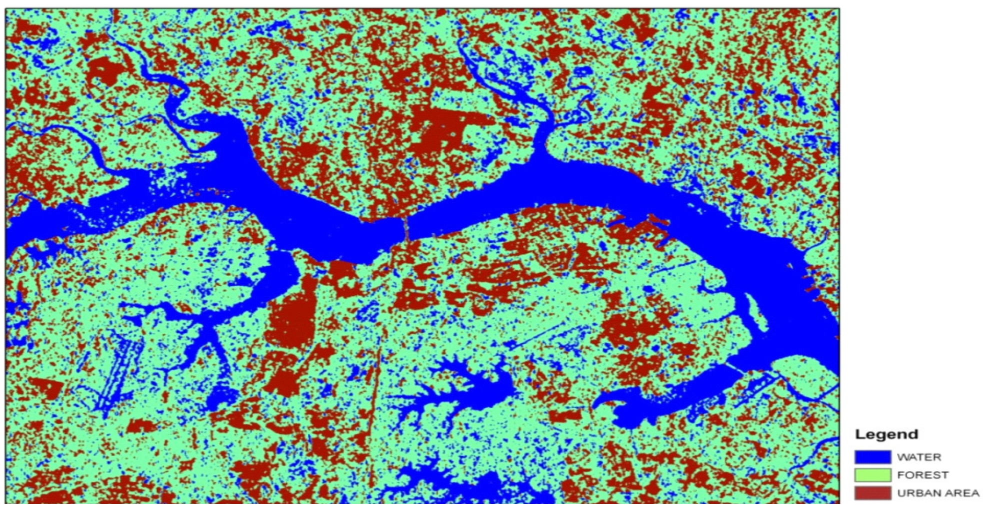

Figure 3. Fuzzy classification map from RADARSAT-1 SAR data.

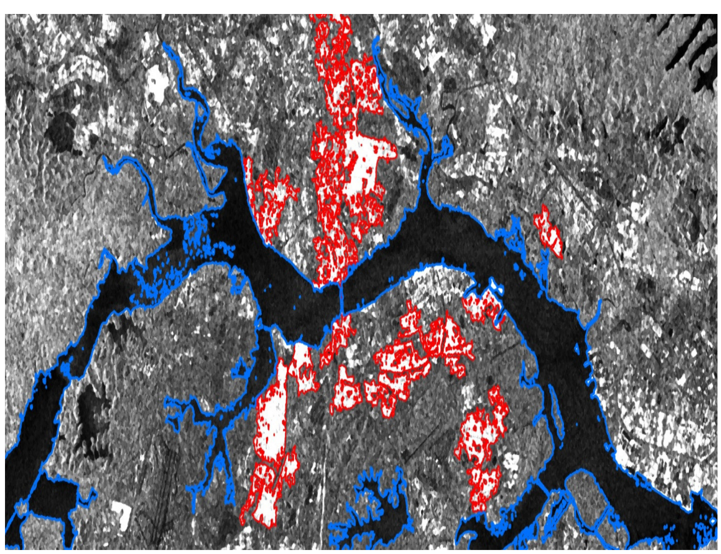

Figure 4. Boundary of urban and water zones in RADARSAT-1 SAR image.

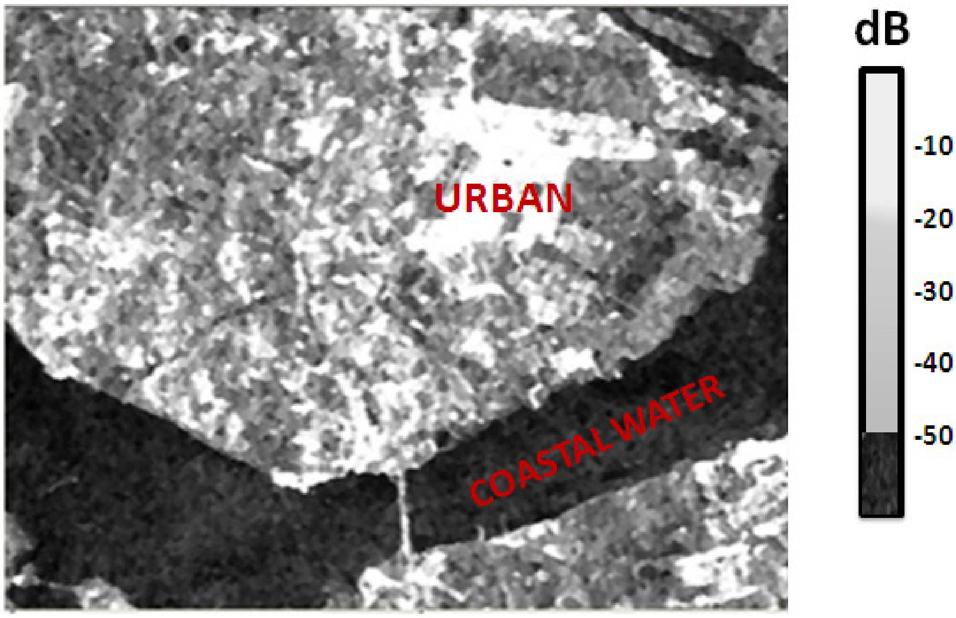

Figure 5. Backscatter variations in coastal waters and urban zones.

bright targets in an image, such as the buildings and other man-made structures in this radar image of a city (Lee, 1981; Ulby et al., 1982).

Conclusion

This work demonstrated technical method for object recognitions in SAR satellite data. In doing so, fuzzy classification and Lee algorithm are implemented to RADARSAT-1 SAR S2 mode data. Clearly, speckle reduction is performed using Lee algorithm. In this context, infrastructures features such as road, bridge, urban zone and coastal water are well identified. Therefore, fuzzy classification provides excellent classification map for coastal and urban zone. The coastal water has smaller backscatter of -50 dB than urban zone. It can be said that the fuzzy classification is best approach for different object classifications and recognitions. In conclusion, the integration between Lee algorithm and fuzzy classification is an excellent technique for land use classifications.

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