Road Identification from Satellite Images based on a Fuzzy Reasoning Model

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ABSTRACT

This paper presents an experimental fuzzy reasoning model for identification of roads in SPOT-4 images with 10 meters resolution in panchromatic mode.
The method consists of two stages: feature extraction and fuzzy modeling for roads identification. In the first stage, a window with size 5x5 convolves over the image to calculate features: mean (*x1*), standard deviation (*x2*), skewness (*x3*), and kurtosis (*x4*). In the fuzzy modeling stage, the roads are identified based on converted features to the specific fuzzy sets in the linguistic variables. In this paper the linguistic variables are **M**ean, **S**tandard deviation, **S**kewness, and **K**urtosis with trapezoid and triangle membership functions. The test areas were samples of SPOT panchromatic images from Iran.

Key words: *fuzzy modeling, SPOT, roads identification, feature extraction*

1. Introduction

Extraction of roads is one of the most important objects in automatic mapping.
A numbers of papers have been published in road extraction (Amini et al 2002, Baumgartner 1999, Gruen and Li 1997). Jedynak et. al.(1995) proposed twenty question for tracking roads in SPOT images. They applied several tests to removed uncertainties. Their method was applied very well on low-resolution satellite images. Gruen et. al. (1997) developed linear feature extraction method using snakes. They combined the characteristics of snakes and adaptive least squares correlation method.
Barzohar and Cooper (1996) proposed an automatic method of extracting main roads in aerial images. The aerial image is partitioned into windows, road extraction start from the window of high confidence estimates, while road tracing is to perform a dynamic programming to find an optimal global estimate. Park and Kim (2001) present a road extraction algorithm using template matching.
Some used semi-automatic methods such as tracking (Mckeown and Denlinger 1988), geometrically constrained template matching (Gruen et al 1995, Vosselman and Knecht 1995) and snakes (Kass et al 1988, Trinder and Li 1995, Gruen and Li 1997). And some used automatic methods (Wiedmann et al 1998, Amini et al 2002, Baumgartner et al 1999, Doucette et al 2001).
Road extraction from images comprises two main tasks:

- *Identification* of roads within an image, which involves image interpretation and feature classification, and
- *Tracking* the roads by precisely determining its outline or centerline.

It is well known that there exist no universal edge detectors that could be applied to a digital image to both identify and track road centerline with equal efficiency. Instead, we typically have operators, which excel in one of these tasks and perform poorly the other. The combination of operators in complex strategies allows us to overcome this problem (Suetens et al., 1992).

In the conventional road extraction methods, the features characterizing the roads are numerical. Images having incomplete specification or noise are usually ignored from the method. In some cases extracting a value of a feature may be more difficult to decide on the relevant extracted features. For this reasons, the method of this paper has used linguistic variables to describe the roads. When we use automatic methods, it is necessary to make identified roads from images. In this paper the author presents an approach to roads identification from satellite images. The approach is based on fuzzy sets theory. Lofti Zadeh initiated fuzzy sets theory in the early 1960s (Zadeh, 1965). In the beginning of the 1970s, Zadeh presents in (Zadeh, 1973) the foundations of linguistic synthesis and shows how vague logical statements can be used to construct computational algorithms, which may be used to derive inferences from vague data. Examples of the use of fuzzy sets theory for object extraction are included in (Mahlander et al 1996) who describe a rule-based methodology, using fuzzy logic, for identification of changes in objects in SPOT Pan images. Kim et al, (1997) present a multilayer perceptron neural net that uses several features of an aerial image for road detection. Shekhar et al., (1996) introduce a knowledge based integration system of image understanding algorithms and present an example of SAR image analysis. (Baumgartner et al., (1997) discuss the use of contextual information for object extraction from digital imagery. Amini et al., (2002) used the fuzzy theory for roads identification from Ikonos images.

In this paper, the features are extracted in the first stage. The features are: *mean (*x1*), standard deviation (*x2*), skewness (*x3*), and kurtosis (*x4*)*. Then a fuzzy reasoning model is applied to classy the features: x_1, x_2, x_3, x_4 into the known feature and then roads identify based on this feature.

The rest of this paper is organized as follows: Section 2 discusses the feature extraction from image. Section 3 explains the fuzzy model for roads identification. Section 4 describes the road identification process and experimental results and finally section 5 presents concluding remarks.

2. Feature Extraction

The most basic of all image features is some measure of image amplitude in terms of luminance, tristimulus value, spectral value, or other units. Amplitude measurements may be made at specific image points, [e.g., the amplitude F(j, k) at pixel coordinate (j, k), or over a neighborhood centered at (j, k)].

This paper used statistical features that show the intensities and intensity variations of pixels. The statistical features have given promising classification results in many satellite image classification tasks, which also motivates their use in land cover/land use classification.

In this research, four measures: mean (*x1*), standard deviation (*x2*), skewness (*x3*), and kurtosis (*x4*), are used as features for a window, *w*, with size 5x5 pixels.

To get information on the shape of the distribution of intensity values within *W*, the skewness and kurtosis are determined. The skewness, *Skew*(*W*), characterizes the degree of symmetry of the intensity distribution around the mean intensity. If skewness is negative, the data are spread out more to the left of the mean than to the right. If skewness is positive, the data are spread out more to the right.

$$skew(w) = \frac{1}{w_x w_y} \sum_{i=1}^{w_x} \sum_{j=1}^{w_y} \left[\frac{w(i,j) - \mu(w)}{\sigma(w)} \right]^3 \qquad (1)$$

Where $\sigma(w)$ is the standard deviation of intensity values in W and $w_x = w_y = 5$.

The kurtosis, *Kurt* (*W*), is the degree of peakness of a distribution, usually taken relative to a normal distribution to avoid particular units.

The normal distribution which is not very peaked or very flat-topped is called *mesokurtic*. The kurtosis of the normal distribution is 3. For this reason, distributions that are more outlier-prone than the normal distribution have kurtosis greater than 3 (*leptokurtic* distribution); distributions that are less outlier-prone have kurtosis less than 3 (*platykurtic* distribution).

$$kurt(w) = \left\{ \frac{1}{w_x w_y} \sum_{i=1}^{w_x} \sum_{j=1}^{w_y} \left[\frac{w(i,j) - \mu(w)}{\sigma(w)} \right]^4 \right\} - 3 \qquad (2)$$

Where $w_x = w_y = 5$.

3. Roads Identification

In conventional roads extraction methods, the features characterizing the input vectors are quantitative (i.e., numerical) in nature. Vectors having imprecise or incomplete specification are usually either ignored or discarded from the design and last sets. Ambiguity in such data may arise from various sources. In some cases the expense incurred in extracting an exact value of a feature may be high or it may be difficult to decide on the most relevant features to be extracted. For these reasons, it may become convenient to use linguistic variables (e.g., small, medium,) in order to describe the feature information. In such cases, it is not appropriate to give on exact numerical representation to uncertain feature data. Rather, it is reasonable to represent uncertain feature information by fuzzy set.

In order to extract an object from images, there are different properties, which describe it. They can be grouped into radiometric and geometric properties. In this paper, we applied fuzzy rules that translate their properties to the specific object, roads. For example:

IF (pixel-gray-level, contrast-from-background) AND (road-geometric-properties) THEN assign-road

The model concentrates on the radiometric properties of roads in this paper. So, the author used the first stage of the above rule for road identification.

In this paper, five linguistic variables are used; **M**ean, **S**tandard-deviation, **S**kewness, **K**urtosis as input linguistic variables and **R**oad as output linguistic variable with their terms as follows:

***M**ean = {Db, Dpg, G, Upg, Ub},*
***S**tandard-deviation = { Db, Dpg, G, Upg, Ub }*
***S**kewness = { Db, G, Ub },*
***K**urtosis = { Db, G, Ub },*
***R**oad = {Db, Dpr, R, Upr, Ub}.*

Where:
Db: Down-bad, Dpg : Down- probably -good, G : Good,
Upg: Up- probably -good, Up : Up-bad , Dpr : Down- probably -road
R: Road, and Upr: Up- probably -road

Note: There is a difference between two sets {mean, standard deviation, skewness, kurtosis} and {**M**ean, **S**tandard deviation, **S**kewness, **K**urtosis}. The first set contains the numerical variables and the second set contains the linguistic variables.

Figure 1 shows the fuzzy model for roads identification. It is based on the input, process, and output flow concept. The model accepts four numerical values: x_1, x_2, x_3, x_4 as input. Their values in the process of the fuzzy model are converted to a meaningful representation (fuzzified) or to their linguistic variables: ***M**ean, **S**tandard deviation, **S**kewness, **K**urtosis*. The fuzzy sets execute all the rules in the knowledge repository that have the fuzzified input in their premise, resulting in the new fuzzy sets that represent the output variable ***R**oad* (***G**ray-Scale*). Finally, the defuzzification stage is used in the model to assign the expected (crisp) value for the output variable. All the membership functions are triangular and trapezoidal functions for simplicity and faster computational time.

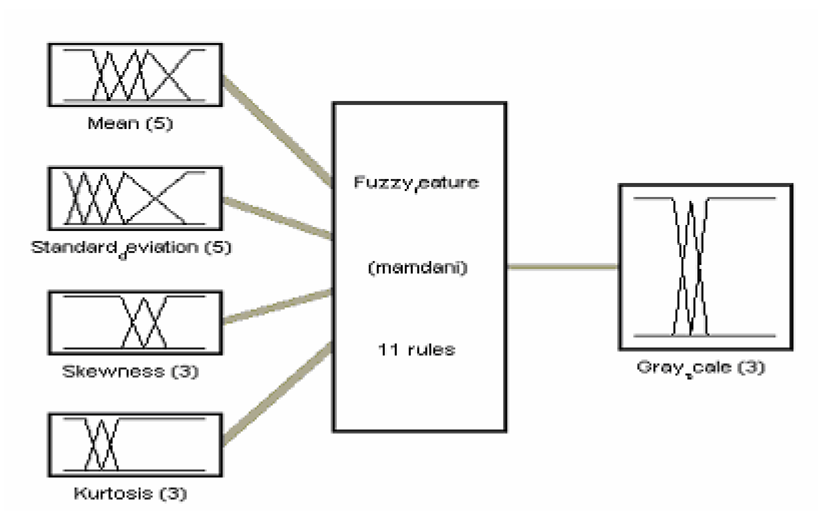

Figure 1 . The fuzzy model for road identification

For more illustration about the algorithm, after reading a pixel of the input images, four features: x_1, x_2, x_3, x_4 are calculated within a window 5x5 centered on this pixel. Their values are converted to the linguistic values. Then rules are applied to produce the final output membership functions. Before the final stage of writing the output gray value of the pixels defuzzification is done to obtain a non-fuzzy or crisp value.

4. Experimental Results

The proposed model has applied to a SPOT-4 panchromatic image with 10 meters resolution from areas of Iran in zone 39. The image contains main roads with wide 2 –3 pixels. Figure 2 shows the image and the results have been shown in figure 3 after execution the method. As you see in figure 3, most main roads have been identified and only a few roads have not been detected. This is due to wide of some roads is less than 2 pixel or the features of the pixels, which belong to roads, are outside the area of suitable fuzzy sets. Also, some pixels are detected incorrectly and they correspond to other objects such as buildings, etc.

Figure 2. Two samples of SPOT images

Figure 3. Resulted images by applying the method

Therefore, automatic road identification from remotely sensed imagery has the potential to save time and money in GIS data collection and update. Improving these approaches and software will be very useful within the remote sensing and GIS communities.

5. Conclusions

In this paper a method developed for identification of roads in SPOT-4 panchromatic images. The motivation of this paper was investigation of potential of fuzzy sets in identification of roads from satellite images.

Different kinds of satellite images (SPOT-4) were used to test the approach. Accuracy assessment of these images demonstrated that the approach was successful. The results indicate that the contrast between road and background effect the quality of the road extraction.

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