ANALYSIS OF NATURAL TEXTURES USING FUZZY TECHNIQUES

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Abstract

The algorithm presented in this paper allows the segmentation of aerial images corresponding to natural scenes, with the aim to detect wood. This detection is made up by analysing the local textures. Due to the fact that natural texture features are very variable, and this variability involves vagueness in feature determination, this work introduces the fuzzy set theory in the representation and analysis of the natural texture features, in order to improve the segmentation and classification of natural images.

Index terms: feature extraction, texture analysis, segmentation, fuzzy sets.

1. Introduction

The problem of aerial images segmentation starts in 70's, analysing the Landsat images [3], [13]. By this reason, during this decade, a great effort was made in the automation of aerial images analysis, due to the amount of information supplied by this satellite. One of the most significant treatments in the segmentation process of these images, is the texture analysis. The first difficulty is to identify different types of textures presents in the image and then to establish the limits between regions having different textures. This is because natural textures don't have dominant patterns and their structure is stochastic.

For the natural texture classification and segmentation several methods have been applied, some of them are: a) Local spatial frequency domain [1],[2]. b) Grey-tone spatial-dependence matrices and second order grey-level statistics [3]-[5]. c) Grey-level run lengths [7]. d) Grey-level difference statistics [13]. e) Spatial texture energy [8]. f) Spatial texture spectrum [9]. Other methods for the measurement of features developed by Haralick [3] are coarseness [10], roughness and directionality [11]. All these methods are based on the analysis of statistical and structural features.

In this work a fuzzy algorithm is presented, which analyses structural and statistical features, because according to the studies [6],[12],[22], methods analysing both, statistical and structural features, give better results.

2. Natural texture approach

The proposed system is divided in three processing stages (figure 1). These stages correspond to a classical scheme where feature extraction plays an important role. Segmentation and classification are made up in single stage because of decision is performed at a pixel level.

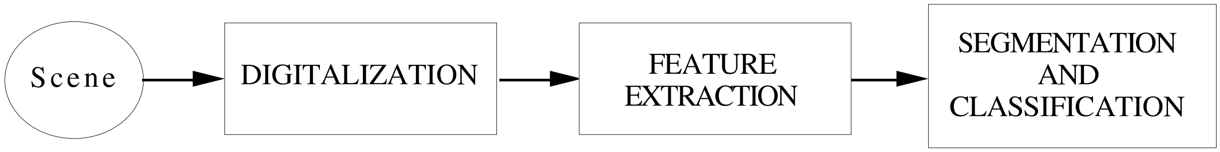

fig.1: Processing Block Diagram

It has been considered, in the present study, a set of textures that are related with the following elements of natural scenes:

Wood.
Scrub.
Roads, tracks.
Fields.
Sown field.
Unsown fields.
Fields of planted trees.

The feature variability of these elements has lead us to replace algorithms based on deterministic techniques by qualitative methods implemented with fuzzy techniques.

2.1 Feature extraction

The feature extraction stage is very important in pattern recognition and image analysis, because of the goodness of the classification depends on the operators used to obtain these features.

Must be considered that wood texture varies depending on: the season, the kind of forest and illumination conditions of the images. So, with the aim of don't increase the additional difficulty in the change of aspect because of the season, in this study only perennial forests are considered.

In this work, the following features are analized to study natural textures:

- Directionality
- Randomness
- Tonality

In order to evaluate these features, the following characteristics of illumination function will be studied:

- Grey level distribution.
- Gradient vector module.
- Gradient vector argument.

Some operators are developed in order to analyse the illumination function characteristics that give the measure of the features. In the main, these operators are robust against the illumination conditions.

Operators definition

a) Directionality: The operator that measures the directionality follows the idea proposed by Tamura[21]. In this sense, we study, in a local way, the histogram of the gradient vector argument.

So, the fuzzy directionality operator, for each pixel (i,j), is given by:

$$\mathrm{dir}(i,j) = \sum_{p=0}^{np-1} \sum_{\phi\in\omega} \mathrm{abs}(\phi - \phi_p)\left((H_{D(i,j)}(\phi_p) - H_{D(i,j)}(\phi)) \Big/ \sum_{\phi=0}^{\pi} H_{D(i,j)}(\phi)\right)^2$$

where:

$$H_{D(i,j)}(\phi) = \sum_{l=i-5}^{i+5} \sum_{k=j-5}^{j+5} a(l,k)$$

and:

$$a(l,k) = \begin{cases} 1 & \text{if } \phi - \pi/9 \le \arg \nabla(l,k) \le \phi + \pi/9 \\ 0 & \text{others} \end{cases}$$

being: $\arg\nabla(l,k)$ the gradient vector argument of the illumination function.
ω the gap, of amplitude $\pi/9$, around ϕ ($\phi\in [0,\pi]$).
ϕ_p the pth peak of the function $H_{D(i,j)}(\phi)$.
np the number of peaks.

b) Randomness: This feature is measured from four parameters. In order to evaluate each parameter, four operators have been developed.
- Difference operator: This operator is given by,

$$\mathrm{dif2}(i,j) = \sum_{l=i-2}^{i+2} \sum_{k=j-2}^{j+2} d_1(l,k)$$

$$d_1(l,k) = (p(l,k)-p(l+1,k))^2 + (p(l,k)-p(l,k+1))^2$$

where p(l,k) is grey level value of the image.

- Average operator: This operator is given by,

$$m_1(i,j) = \frac{\sum_{l=i-2}^{i+2} \sum_{k=j-2}^{j+2} d_2(l,k)}{25}$$

$$d_2(l,k) = (p(l,k)-p(i,j))$$

where p(l,k) is grey level values of the image.

- Deviation operator: This operator is given by,

$$\sigma_1(i,j) = \frac{\sum_{l=i-2}^{i+2} \sum_{k=j-2}^{j+2} (d_2(l,k) - m_1(i,j))^2}{25}$$

- Gradient module operator: This operator is given by,

$$\mathrm{dif\ mod}\nabla(i,j) = \sum_{l=i-2}^{i+2} \sum_{k=j-2}^{j+2} \mathrm{dif}(l,k)$$

$$\mathrm{dif}(l,k) = \left(|\nabla p(l,k)| - |\nabla p(l+1,k)|\right) + \left(|\nabla p(l,k)| - |\nabla p(l,k+1)|\right)$$

where $|\nabla p(l,k)|$ is the gradient vector module of the illumination function.

c) Tonality: This feature is measured from two parameters. To evaluate them, two operators has been developed.

- Average tonality operator: This operator is given by,

$$m_2(i,j) = \frac{\sum_{l=i-5}^{i+5} \sum_{k=j-5}^{j+5} p(l,k)}{121}$$

- Deviation tonality operator: This operator is given by,

$$\sigma_2(i,j) = \frac{\sum_{l=i-5}^{i+5} \sum_{k=j-5}^{j+5} (p(l,k) - m_2(i,j))^2}{121}$$

2.2 Segmentation and classification

Obtaining fuzzy rules

In order to obtain fuzzy membership functions we define six rules using the operators defined in the previous section. The value of operators used in fuzzy rules has been determined by heuristic methods, from analyzing a set of images. In this way, for each pixel in the image, we'll obtain six membership degrees.

Rules and membership functions:

R1: The membership of pixel (i,j) to the wood fuzzy set, is greater as long as the average $m_2(i,j)$ is closer to the interval [40,75].
Then, μ_{R1} is given by

$$\mu_{R1}(i,j) = \begin{cases} 0 & \text{if } m_2(i,j) \leq 30 \text{ or } 85 \leq m_2(i,j) \\ 1 & \text{if } 40 \leq m_2(i,j) \leq 75 \\ \frac{1}{10}(m_2(i,j)-30) & \text{if } 30 < m_2(i,j) < 40 \\ 1-\frac{1}{10}(m_2(i,j)-75) & \text{if } 75 < m_2(i,j) < 85 \end{cases}$$

R2: The membership of pixel (i,j) to the wood fuzzy set, is greater as long as the operator dif2(i,j) is closer to the interval [2200,8000].
Then, μ_{R2} is given by

$$\mu_{R2}(i,j) = \begin{cases} 0 & \textit{if } dif2(i,j) \leq 2000 \textit{ or } 8500 \leq dif2(i,j) \\ 1 & \textit{if } 2200 \leq dif2(i,j) \leq 8000 \\ \frac{1}{200}(dif2(i,j)-2000) & \textit{if } 2000 < dif2(i,j) < 2200 \\ 1-\frac{1}{200}(dif2(i,j)-8000) & \textit{if } 8000 < dif2(i,j) < 8500 \end{cases}$$

R3: The membership of pixel (i,j) to the wood fuzzy set, is greater as long as operators that measure grey level distribution, $m_1(i,j)$ is closer to the interval [100,1000] and $\sigma_1(i,j)$ is closer to the interval [60,500].
Then, μ_{R3} is given by

$$\mu_{R3}(i,j) = \begin{cases} 0 & \textit{if } 470 \leq D_1(i,j) \\ 1 & \textit{if } D_1(i,j) \leq 450 \\ 1-\frac{1}{20}(D_1(i,j)-450) & \textit{if } 450 < D_1(i,j) < 470 \end{cases}$$

where $D_1(i,j) = \sqrt{(m_1(i,j)-550)^2 + \left(\frac{45}{22}(\sigma_1(i,j)-280)\right)^2}$

R4: A pixel (i,j) belongs to the wood fuzzy set, if σ_2(i,j) is lower than 8.
Then, μ_{R4} is given by

$$\mu_{R4}(i,j) = \begin{cases} 0 & \text{if } 10 \le \sigma_2(i,j) \\ 1 & \textit{if } 0 \le \sigma_2(i,j) \le 8 \\ 1-\frac{1}{2}(\sigma_2(i,j)-8) & \textit{if } 8 < \sigma_2(i,j) < 10 \end{cases}$$

R5: The membership of pixel (i,j) to the wood fuzzy set, is greater as long as the operator dif(i,j) is closer to the interval [150,500].
Then, μ_{R5} is given by

$$\mu_{R5}(i,j) = \begin{cases} 0 & \textit{if } \mathrm{dif}(i,j) \le 100 \text{ or } 600 \le \mathrm{dif}(i,j) \\ 1 & \text{if } 150 \le \mathrm{dif}(i,j) \le 500 \\ \frac{1}{50}(dif(i,j)-100) & \text{if } 100 < \mathrm{dif}(i,j) < 150 \\ 1-\frac{1}{100}(dif(i,j)-500) & \text{if } 500 < \mathrm{dif}(i,j) < 600 \end{cases}$$

R6: A pixel (i,j) belongs to the wood fuzzy set, if the operator dir(i,j) is greater than 0.9 and if the module gradient vector mod∇(i,j) is lower than 15.
Then, μ_{R6} is given by

$$\mu_{R6}(i,j) = \begin{cases} 0 & \textit{if } 20 \le \mathrm{D}_2(i,j) \\ 1 & \text{if } \mathrm{D}_2(i,j) \le 15 \\ 1-\frac{1}{5}(D_2(i,j)-15) & \text{if } 15 < \mathrm{D}_2(i,j) < 20 \end{cases}$$

where

$$D_2(i,j) = \begin{cases} \mathrm{mod}\,\nabla(i,j) & \text{if } \mathrm{dir}(i,j) > 1{,}5 \\ \sqrt{\mathrm{mod}\,\nabla(i,j)^2 + (25(\mathrm{dir}(i,j)-1{,}5))^2} & \text{if } \mathrm{dir}(i,j) \le 1{,}5 \end{cases}$$

Obtaining membership degree

With the aim of define the membership degree of a pixel to the wood fuzzy set, an aggregation function is performed through membership functions defined in previous section, having also into account that a pixel belongs to the wood fuzzy set if its neighbourhood satisfies:

- There is a random distribution of the gray levels.
- There is no directionality.
- Evaluating the feature tonality, the grey level average m1 is between certain values, or the deviation $\sigma 2$ is inside a certain interval .

So, the aggregation function used is the following:

$$\mu_R(i,j)=\text{mín}(\text{máx}(\mu_{R1}(i,j),\mu_{R4}(i,j)),\ 1-\mu_{R6}(i,j)\ ,\ \text{máx}(\mu_{R2}(i,j),\mu_{R3}(i,j),\mu_{R5}(i,j))).$$

3. Results

The algorithm has been applied to multilevel images (256 grey levels). These are aerial images, with a resolution of 512x512 pixels, where a pixel represents 2,5 m^2.

Figures 2 and 3 show the analised images, the first one has forest areas (dark areas), paths, agricultural and urban areas. The second shows sown fields, paths, vineyards and forests.

The results after an α-cut over the aggregation function, applied to images in figures 2 and 3, are shown respectively in figures 4 and 5, where black area has been identified as *wood* and other elements have been identified in white colour. As it can be seen in the resulting images, promising results are obtained, although it is difficult to measure the goodness of the classification, because if these images had been analysed by two human experts, results obtained would be different due to the subjectivity component present in the delimitation of the boundaries between the different textured regions.

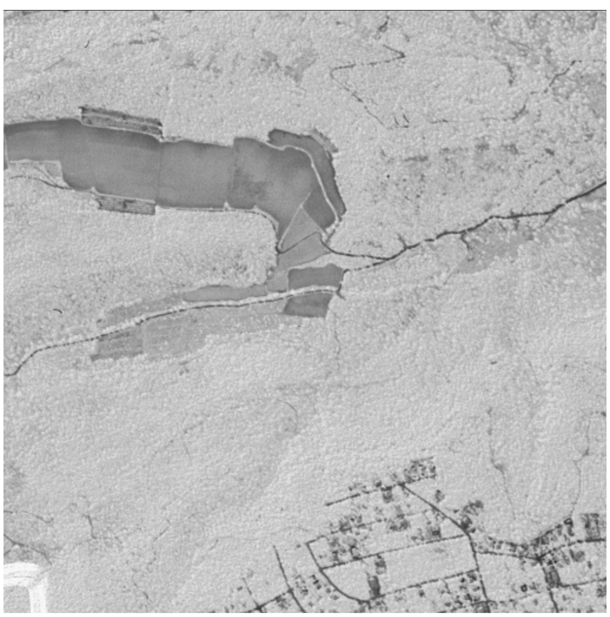

fig.2: Image with urban area, wood, sown fields and paths.

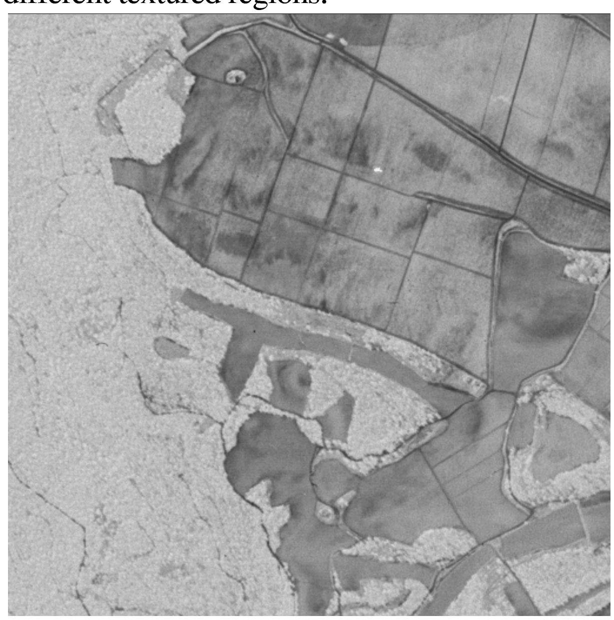

fig.3: Image with wood, vineyards and paths.

fig.4: Results of wood classification of the image showed in figure 2.

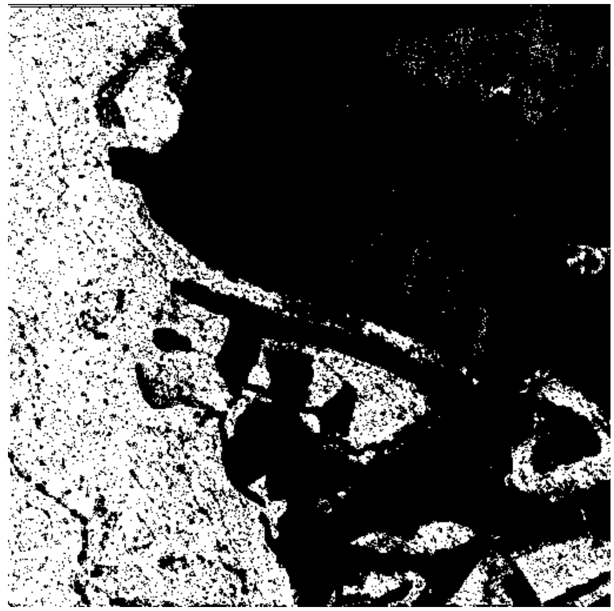

fig.5: Results of wood classification of the image showed in figure 3.

4. Conclusions

Some operators have been deduced that evaluate the given observed features in wood and classify every pixel in the image inside the *wood fuzzy set*. These operators as well as their values used in fuzzy rules are determined by the resolution of the treated images, so that for another set of images with different resolution it would be necessary to readjust the structure of the operators. However, the classification algorithm of wood is invariant to the change of resolution, also it's invariant to rotations and translations, due to operators measure structural component of the textures. Moreover, the operator that measures directionality feature, from gradient vector argument, is robust to noise.

The application of fuzzy methods for classification of natural texture is very suitable because of the inherent vagueness to the feature definition of the studied textures, such as randomness and directionality.

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