ANALYSIS OF IMAGE SEGMENTATION OF MULTISOURCE DATA IN MOUNTAIN ENVIRONMENTS

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ABSTRACT

In this work, a multisource features set for classification of landscape and, more specifically, forestry environments, is proposed and evaluated. Spectral features are obtained from Landsat-TM images; textural features are extracted from panchromatic high resolution aerial images, and digital elevation models are used to generate insolation maps. The data were georreferenced and resampled maintaining their initial spatial resolution. TM bands and a standard vegetation index (NDVI) were used as spectral variables. The texture was characterized by features extracted from the gray level co-occurrence matrix, several textural energy factors and a edgeness index. In the calculation of the insolation map, the integration of the projection of shadows due to the relief along the year and in different times in the day was considered.

Since the texture variables have a high degree of correlation, and many combinations of parameters can be employed for their calculation, a selection of the optimal parameters was carried out by means of stepwise discriminant analysis techniques. In order to compare the improvement due to the multisource classification, four segmentation processes were applied over the test images: using only the spectral features, only the textural features, using the textural features and the insolation, and finally integrating the three sets of variables.

The classification processes were first evaluated over a testing set of subimages selected on the working areas. Each set of subimages was representative of a vegetation class, characterized by different botanical species, density or spatial distribution of the vegetation. This first evaluation was useful to find out what classes were able to be discriminated with those selected features, without considering other specific aspects dependent upon the limitations of the classifier used. Then, evaluation of the segmented image provided an idea of the classification of the studied areas. Texture features are valuable for identification of dense forest areas and olive fields from mediterranean bush landscapes. Introducing information obtained from the digital elevation model, the overall classification accuracy increases in almost a 5% and sparse vegetation classes are better distinguished. The textural variables also complement the spectral information provided by the TM sensor, and allow to increase the spatial detail of the resulting vegetation maps. The method used for characterizing the boundaries between textures, based on the analysis of four diagonal neighborhoods, have a high computation cost, but provide a significant improvement of the accuracy on these particular areas.

The tests provide encouraging results for the integration of spectral, spatial and topographic information applied to the study of vegetation, particularly that aimed to characterize spontaneously grown mediterranean forestry, where the relief and orientation are important factors, and where their differences are reflected on the spatial distribution and density of plants. The proposed methodology is potentially useful for the automatic production and updating of thematic cartography at different levels of detail, but it needs to be applied over a variety of landscape areas, and some post-segmentation techniques have to be developed and investigated for practical uses.

1 INTRODUCTION

Accurate classification of landscape units using remote sensing data is usually limited by several factors. Some of them are landscape related, such as the pattern heterogeneity and inherent variability of the units to be discriminated, while some other factors are dependent upon the type of data available, such as the spatial, spectral and temporal resolutions of the sensors. Some of these factors are interrelated. Thus, the distribution of gray levels or pattern shown by one unit is closely dependent on the spatial resolution of the image. Therefore, to accomplish the classification tasks with a certain degree of accuracy, different and complementary sources of data must be used. Some previous works have combined multispectral and terrain data to improve landscape characterization (Florinsky, 1998), and texture analysis has been used in combination with spectral data to improve the image classification processes. Ruiz et al. (1999) reported the feasibility of classifying, with a promising degree of accuracy, mountain mediterranean landscapes using texture features, and the increase of a 5% on the global accuracy introducing the insolation factor, but the classification was made over single samples of small areas, individually, without a global segmentation process on the images.

In this study, four segmentation processes were applied over the test images: using only the spectral features, only the textural features, using the textural features and the insolation, and finally integrating the three sets of variables. The main goal was to quantify the improving of mountain scenes classification by adding different sets of georreferenced variables.

2 INITIAL DATA

The spectral data used was a multispectral Landsat-TM scene of the area, located on the west of the province of Valencia (Spain), characterized by a meso-mediterranean landscape, mainly covered by forest and shrub, and some occasional sparse mountain crops. Three aerial photographs (scale 1:25.000) were used for the study, and a digital elevation model, with a spatial resolution of 25 m. Figure 1 shows one of the aerial image used on the tests.

Figure 1.- Aerial photograph of the area of study.

3 METHODS

The figure 2 shows the flowchart of the methodology applied: preprocessing, texture analysis, insolation map derivation from DEM. These aspects will be described on the next paragraphs.

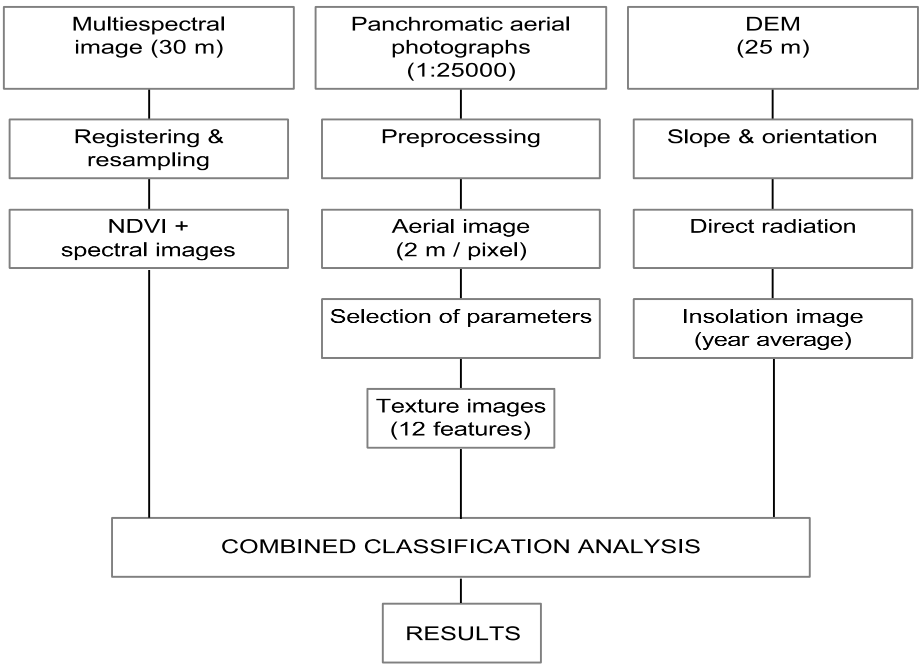

Figure 2. Methodology used for the analysis.

3.1 Preprocessing

The aerial photographs were digitized and resampled to 2 m/pixel, and radiometrically adjusted to each other by means of a lineal transformation based on the means and standard deviations of their histograms. The multispectral image was registered taking the aerial images as a reference. Then, the resolution was virtually increased to 2 m, so it could be processed later with the texture images.

3.1.1 Subsubsection Header. Main body of the text

3.2 Texture analysis

A total of 12 texture features were computed from the 2m resampled aerial imagery. Eight of these features were obtained from the grey level co-occurrence matrix (GLCM), as proposed by Haralick et al. (1973), namely: *uniformity, entropy, contrast, mean, variance, inverse difference moment, product moment* and *correlation*. A textural *edgeness* variable was computed based on the idea of Sutton and Hall (1972), consisting on the conception of texture in terms of edgeness per unit area and represented by the gradient (the sum of the absolute value of the differences between neighbouring pixels) as a function of the distance between the pixels. For every distance *d* (tested as a variable texture parameter) and subimage *I* , defined over a neighbourhood *N*, the following expression was computed :

$$g(d) = \sum_{(i,j)\in N} \{ |I(i,j) - I(i+d,j)| + |I(i,j) - I(i-d,j)| + |I(i,j) - I(i,j+d)| + |I(i,j) - I(i,j-d)| \}$$

where *g(d)* represents the *edgeness* per unit area of a particular pixel on the image.

In addition, three textural *energy* indexes were computed by convolving the initial image *I* with three kernels, yielding three new images $J_n = I * g_n$ $(n = 1,...,3)$. For each of these images, the global textural *energy* value for each pixel in a 7 x 7 neighbourhood was obtained using the expression :

$$S_n(r,c) = \frac{1}{49} \sum_{i=-3}^{3} \sum_{j=-3}^{3} | J_n(r+i, c+j) |$$

Since this process is operated in relatively large neighbourhoods, a problem associated with this approach is the introduction of significant errors along the boundaries between different textures in the image. For instance, it might be the case of obtaining energy values in boundary areas that are closer to a third texture than to the ones included in the 7 x 7 window, with the subsequent error in classification. In order to reduce this effect, for each pixel on the textural energy image J_n, the mean and variance of the four neighbourhoods for which the pixel is the corner were computed, and the new pixel takes the value of the mean of the quadrant that has the smallest variance. Three different kernels were used to obtain the convolved images yielding the three textural energy features used : L5 = [1 4 6 4 1] gives some information of the grey level, S5 = [-1 0 2 0 -1] enhances certain shapes on the grey level dimension, R5 = [1 -4 6 -4 1] enhances ripple shapes on the image.

Six ***classes*** were defined according to the type of spontaneous vegetation of the studied region, as well as to the density and pattern in which the vegetation is arranged:

- *Dense forest* (DF): composed of spontaneous trees (pines, oaks,...) providing a complete coverage of the surface.
- *Medium density forest* (MF): Similar but roughly covering between the 40 and 60% of the surface.
- *Dense shrub* (DS): spontaneous mediterranean shrub combined with mixed herbaceous vegetation, covering more than the 70% of the surface.
- *Medium and low density shrub* (MS): similar but with an interval of coverage ranging from 30 to 70%.
- *Mountain crops* (CR): this class is mainly composed by small olive and almond trees plantations disposed on the mountainsides forming terraces.
- *Barren soil* (BS): fallow land, rocks and, in general, non -vegetated soils.

The figure shows six samples or sub-images representatives of the six classes defined.

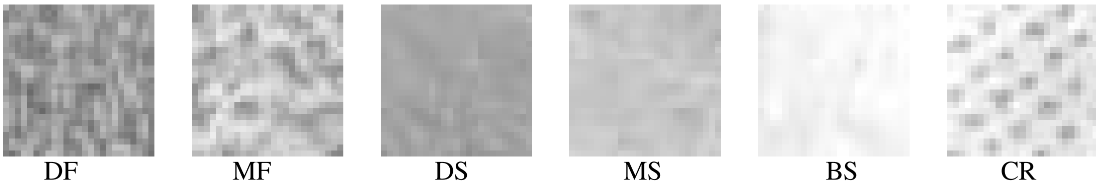

Figure 3.- Six samples of the classes used for classification.

Three different texture parameters were tested and evaluated : 1) *window size* of the neighbourhood to be considered in the texture segmentation ; 2) *number of grey levels* to use in the computation of the GLCM ; and 3) *distances* between neighbouring pixels when computing both, the GLCM and the *edgeness* index. Three squared window sizes were tested of 10, 13, 19 and 25 pixels. Larger window sizes would have an undesirable stronger boundary effect in the texture classification. Four number of grey levels (8, 16, 32 and 64), and four different distances (1, 2, 3 and 4 pixels) were also evaluated.

For selection of optimal features and parameters, the first step was the definition of training samples obtained from each texture class to be discriminated. Series of 25 samples per class were defined, trying to be representative of the class and homogeneously distributed over the area of study.

The grey level co-occurrence matrices were computed in four directions quantized to 45º intervals. Since the defined classes did not present any directional tendency, the results of the four directions were averaged, obtaining 64 co-occurrence matrices per subimage, that is, all the possible combinations between the parameters tested : 4 distances, 4 window sizes and 4 ranges of grey levels.

Because of the high correlation between some of the texture variables, specially those obtained from the GLCM, a procedure of *forward stepwise discriminant analysis* was applied to select the optimal features and parameters and to preview the separability of the texture classes.

A prior classification process of the subimages, based on discriminant analysis techniques, was performed, so the optimal texture parameters were defined attending to the criterium of maximizing the discriminant power. In addition, this process would allow to preview the performance of the different texture variables, helping to choose the ones better adapted to the problem.

3.3 Extraction of data from DEM

A digital elevation model (DEM), with a grid every 25 m., was used to obtain a insolation image of the area, considering that the solar radiation that arrives to a point located out of the atmosphere in a given moment depends on the sun elevation and azimuth, the latitude of the point, its slope and orientation. Thus, the projected shadows along the year can be calculated from the topographic data, so it is possible to estimate the potential radiation arriving to each point on the terrain. The integration of the radiation values along the year, achieved using significant instants between the two solstice, allows to obtain the final average insolation map (Figure 4) . This map is, therefore, based on the slope and orientation obtained from the DEM, on the latitude, and on the sun position for 105 different moments, and it is expressed in terms of direct solar radiation. The complete methodology used has been reported in previous works (Ruiz et al., 1999; and Pardo et al., 1999).

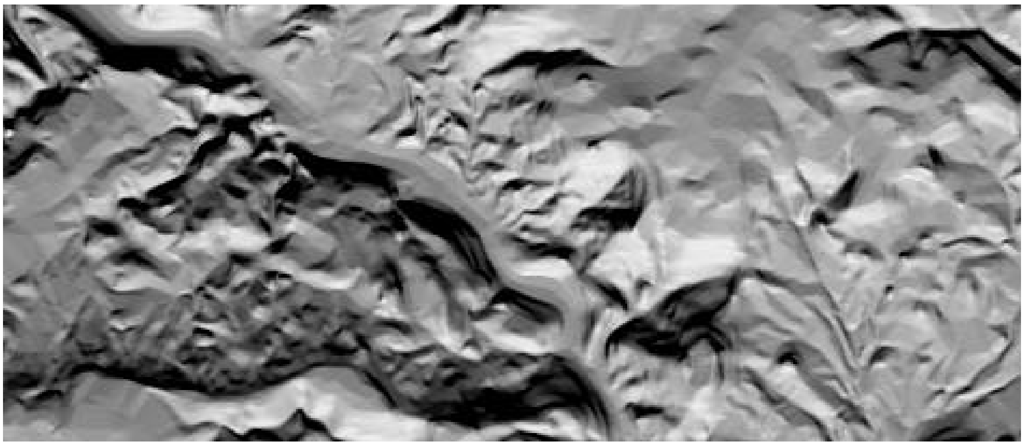

Figure 4.- Insolation image obtained from the DEM.

3.4 Comparative classification analysis

In order to accomplish the main objectives of this work, that is, to evaluate the texture classification of some specific forest areas using exclusively aerial panchromatic images; and to assess the increase of accuracy on the classification by adding both insolation images and spectral variables (NDVI and direct infrared and visible bands), a comparative classification analysis, was designed. In all the cases, the images were classified using the maximum likelihood method. In the first test, the classification was made using just spectral data: four of the TM bands: three infrared (excluding the thermal band) and the red one, and the NDVI. The second test was classified using only the six texture most discriminant variables, obtained after the previous stepwise discriminant analysis and the Jeffries-Matusita distance based separability analysis. In a third test, the insolation band was added to the former texture variables. Finally, a fourth classification was applied using the three groups of data: spectral (only NDVI), texture and DEM extracted.

4 RESULTS AND CONCLUSIONS

The table --- shows the results of the comparative analysis considering three different points of view: producer, user and overall accuracy. From the overall accuracy results, it may be deduced that the spectral data by themselves are not sufficient to obtain good classification results, the texture is more appropriate due to the heterogeneity of classes and to the high spatial resolution required. The insolation variable adds some information to the texture in general, but is specially noticeable in the spontaneous classes with spontaneous shrub, where this factor seems to affect the density of vegetation.

	PRODUCER´s ACCURACY				USER's ACCURACY			
CLASS	*NDVI+ spectral*	*texture*	*texture + insolation*	*text. + ins. + NDVI*	*NDVI+ spectral*	*texture*	*texture + insolation*	*text. + ins. + NDVI*
DF	88.99	81.57	83.95	87.00	87.65	93.62	94.40	94.47
MF	69.58	90.07	91.95	91.67	83.67	70.84	75.72	80.80
DS	77.77	66.70	73.00	81.41	68.21	81.29	84.78	90.78
MS	86.70	82.81	83.04	89.57	86.66	80.93	78.61	83.10
BS	76.41	96.17	97.00	98.95	87.65	98.86	98.87	99.14
CR	97.65	96.64	96.78	97.56	85.36	98.11	98.92	98.97
Overall accuracy	**83.08**	**85.66**	**87.74**	**90.60**				

Table 1.- Results of the classification comparative analysis, containing information about overall, producer and user accuracy.

Figure 5 shows, on a graphical representation, the results of accuracies for each of the six classes considered. Notice the increase of accuracy obtained for spontaneous classes when the texture information is added.

The segmentation of the mountain environments studied is improved when progressive and complementary data are added as new variables, regarding spectral, textural and DEM data. However, it must be pointed that texture classification introduces a certain degree of error in those areas located between classes, because of the neighbouring effect. In this sense, it is necessary to develop a method to reduce this effect, specially noticeable when large window sizes are used. The proper combination of multisource georreferenced data offers promising possibilities for the segmentation of mountain classes, specially important on those areas with a landscape characterized by a very heterogeneous spectral classes and arrangement of landscape units.

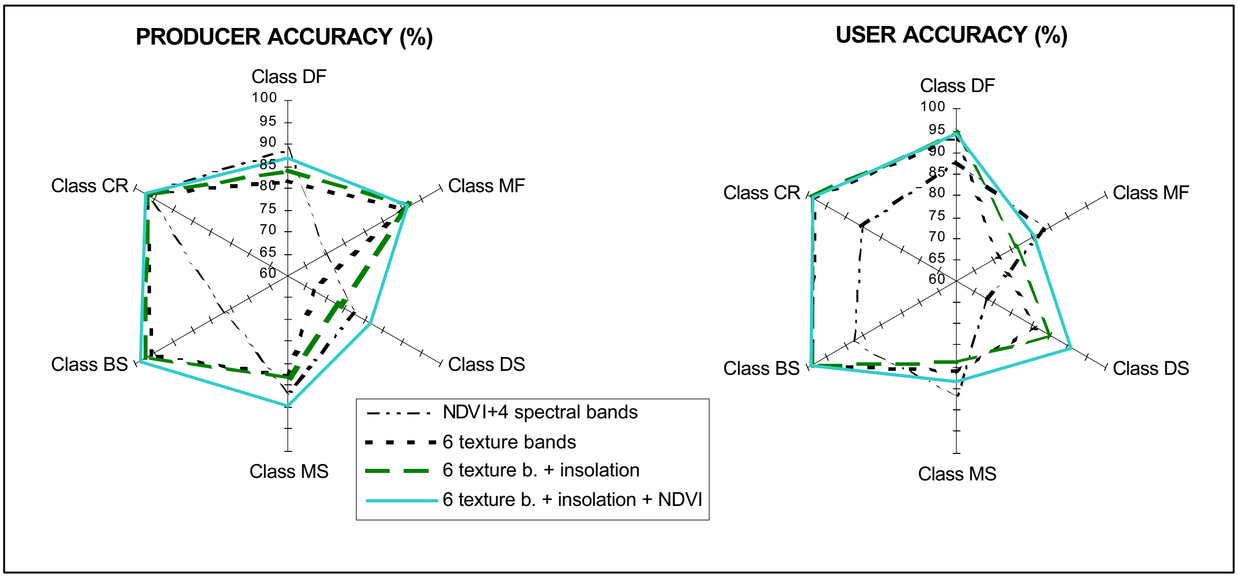

Figure 5.- Graphical representation of the comparative classification analysis for the four different tests performed.

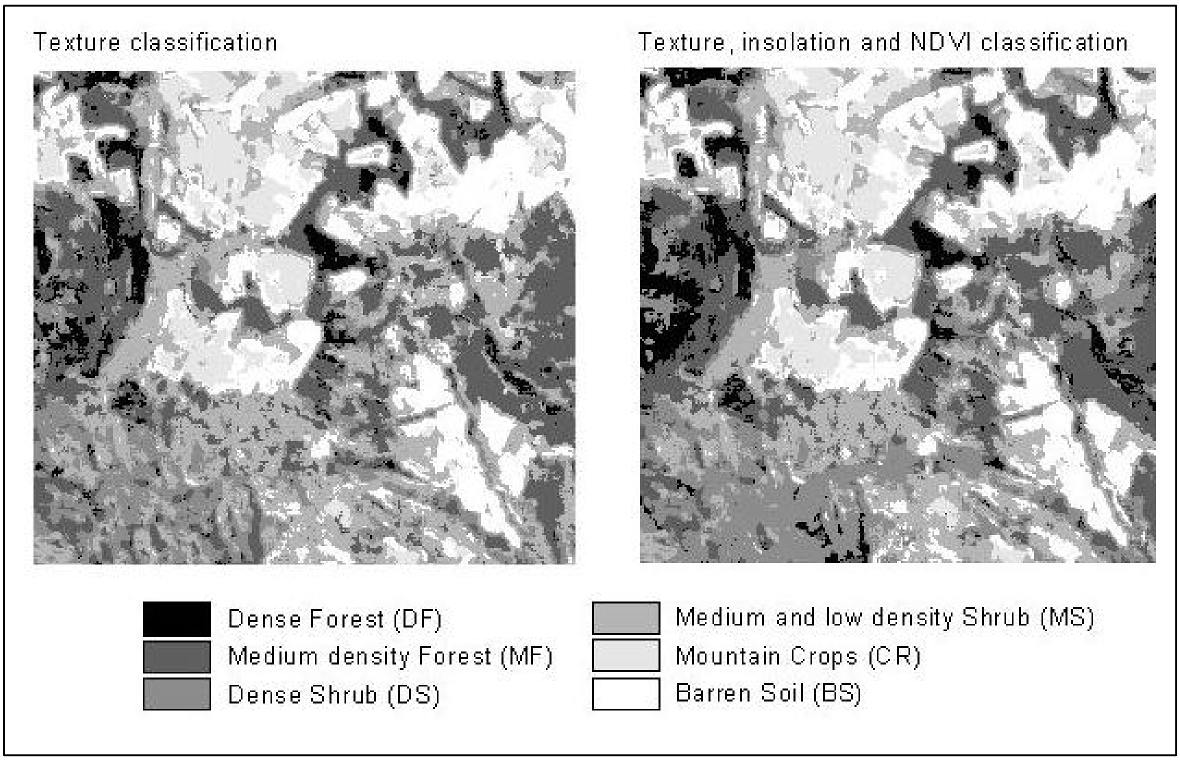

Figure 6.- Classification maps obtained using only texture bands (left) and the three groups of variables (right) on the area represented by the aerial photograph on figure 1.

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