AUTOMATED TECHNIQUES FOR SATELLITE IMAGE SEGMENTATION

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ABSTRACT

In this paper a combined method between "classical" and automatic approach for remote sensing image analysis is presented. Typically, satellite images are used in order to detect the distribution of vegetation, soil classes, built-up areas, roads, and water body as rivers, brooks, lakes, ecc. Referring for example to Landsat-TM images, the identification of such aspects is performed through the "classical" approach of image classification. Basically, it deals with the use of pseudocolors and/or combinations of various spectral bands to acquire different thematic layers from the images. In this work a further processing step is introduced, namely a segmentation algorithm is applied to color images in order to improve the image analysis both from qualitative and quantitative point of view. This algorithm belongs to the class of operations performed in the automatized unsupervised analysis of color images. Last recent advances in the field of computer science and CPU performance have lead to a great reduction of data processing times, allowing therefore to apply also in the field of Remote Sensing more complex algorithms. The proposed segmentation algorithm is based on a feature-space approach and implements two processing techniques: the "histogram thresholding" [1] and the "clustering" [2]. Some interesting results applied to Remote Sensing images will be provided.

1. INTRODUCTION

So far, tipical approach to remote sensed data analysis has been based on the use of different linear combinations between available spectral bands or creating new ones. In this phase satellite data are processed through the activity of a human operator, which using RGB filters tries to identify several classes of elements appearing on them. These classes are therefore a way to group homogeneus land features, such as urban areas (roads, buildings, etc.), vegetation (woods, cultivated and uncultivated soils) and water areas (rivers, lakes, etc.). These layers are often represented in terms of pseudocolor images, in order to better highlight a specific feature distributed along the land.
The basic concept underlying that procedure is similar to the image segmentation, the first step for the digital image processing normally adopted in the field of Computer Vision. This operation is performed through the partitioning of an image just in homogeneous and separated regions. So far, segmentation techniques were applied only to gray scale images, though the color information would allow a more complete image representation. In fact, the application of this method was limited mainly by the computational time spent for color data processing, larger than the one needed for gray color data. Today, recent advances in the field of computer science and CPU performance, have lead to a great reduction of data processing times, allowing therefore to apply these segmentation algorithms to the field of Remote Sensing, as well. Several color image segmentation algorithms are nothing but the development of previous gray color procedures, others are instead new *ad-hoc* techniques for color data, which take into account the physic relationship between light and coloured materials. Such algorithms work in well defined color spaces, such as RGB , HSI or HSV. Anyway these reference frames are not uniform, i.e. color differences of same entity, as perceived or "measured" by human eye, are not converted in similar distances among the points representing such colors in the above mentioned spaces. These problem has been overcome by introduction of uniform color spaces, such as C.I.E.L*u*v* and C.I.E.L*a*b*.
Adopted color image segmentation algorithms can be classified as follows:

- Feature-space based, working on the space of coloured figures in the image
- Image-domain based, i.e. they analyse the image geometry and color
- Physics based, involving the physic relationships between light and materials

In this work, a segmentation algorithm belonging to the first class was applied to remote sensed images in order to improve qualitatively and quantitatively the result of the "classical" approach. This means, assuming that different classes of land features are already identified through classical methodology, a further analysis step is introduced by application of proposed algorithm to refine the results of previous phases. The main advantage of this approach rely on the fact that the algorithm is unsupervised, therefore it doesn't require any *a-priori* information and can be fully automatized.
The paper is structured as follows: in section 2 a brief overview of feature-space based techniques is reported, then in section 3 the proposed algorithm is explained. Some results of its application to remote sensed images are presented in section 4, while section 5 deals with the conclusions.

2. THE FEATURE-SPACE BASED TECHNIQUES

Assuming that color is a constant property of the surface of each object appearing on the image, the image segmentation can be addressed through two following different strategies: *clustering* and *histogram thresholding*.

In the first technique, image pixels are firstly mapped on a certain color space, in order to convert pixels to points. Then these points are grouped in different sets (clusters) on the ground of color information of each corresponding pixel. In this way, given the above mentioned assumption, the different objects of the image can be discriminated in terms of these clusters or cloud of points. The distribution of the points inside each cluster depends mainly upon the color change, due to shading effects and noise of the acquisition device. It should be noted that the clustering technique belongs to the *unsupervised* classification algorithms, since no a-*priori* knowledge about the image is required. An example of clustering implementation is provided by the k-means algorithm: it is widely used not only for color image segmentation but also for applications involving vectorization and data compression.

The histogram thresholding algorithm belongs to another class of segmentation techniques, early applied to gray scale images. In this method image pixels are not mapped on a color space, but rather some *ad-hoc* histogram of color figures, such as the Hue, are generated. Through that model, objects on the image will be identified as peaks of the histogram, while the background will correspond to its depressions. In the field of color images a thresholding algorithm involves a bit more complex implementation, since it has to work in a 3D color space, meaning that a 3D histogram has to be taken into account. Furthermore, in this case histogram profiles become quite jagged with spurious peaks, which make the segmentation more ambiguous.

The proposed method is based on a combination of the clustering and histogram thresholding techniques. In summary, given a remote sensed image, the representative color are firstly identified by looking for the major color groups, through the histogram thresholding of the Hue information. Then, the larger clusters in the planes of constant Hue are determined, through the k-means clustering algorithm.

3. THE SEGMENTATION ALGORITHM

The segmentation process works in the C.I.E.L*u*v* uniform color space, provided with euclidean norm $\|L^*u^*v^*\| = |(L^*)^2+(u^*)^2+(v^*)^2]^{1/2}$. In this space a cilindric coordinate reference system was introduced (H_{uv}*, C_{uv}*, L*), whose Hue angle is defined as $H_{uv}^*=\arctan(v^*/u^*)$, the crominance as $C_{uv}^*=[(u^*)^2+(v^*)^2]^{1/2}=L^*\bullet S$ and the saturation as $S=([(u^*)^2 + (v^*)^2]^{1/2})/L^*$. The clustering method, based on anisotropic diffusion, is a non-linear filtering technique, which performs a more high selective smoothing in omogeneus regions and almost null on the egdes, while it retains all the edge-related information. In this algorithm Hue H(x,y,t) and Saturation S(x,y,t) are represented as one complex quantity, the "crominance " function K(x,y,t)=S(x,y,t)exp(j H(x,y,t)), which is in turn diffused, clustered and segmented. The modeling of Hue and Saturation in the same function takes into account the physic relationship existing between them. It is well known that Hue changes are negligible for low values of Saturation, but noticeable for high values. The same operations are applied to the lightness function L*, which is however processed separately.

The combination of this two parallel segmentation tasks leads to a partitioned color image. The overall scheme of developed algorithm is showed in Figure 1.

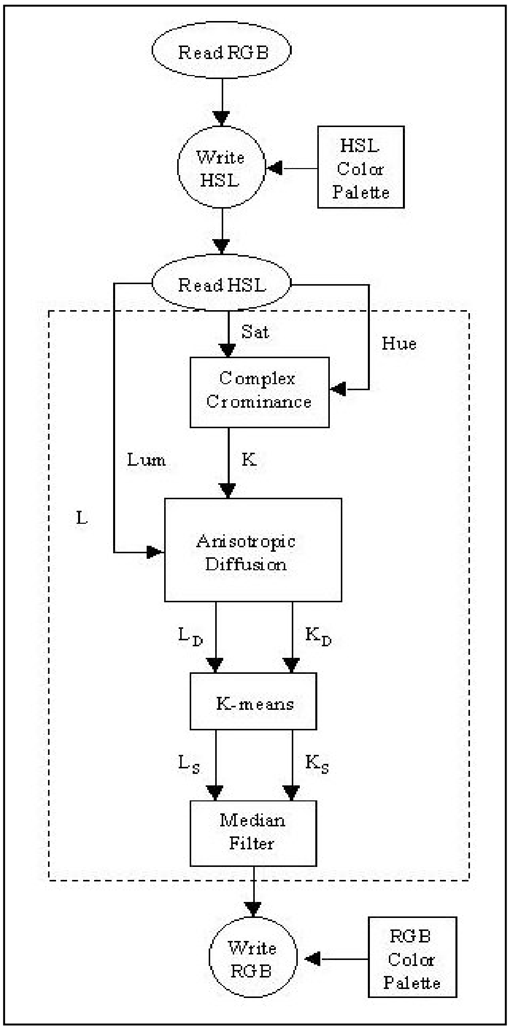

Figure 1: Scheme of the segmentation algorithm in the dashed box

The anisotropic diffusion has been numerically implemented through the partial derivative equation of heat diffusion, as stated below:

$$\partial K(x,y,t)/\partial t = div[c(x,y,t)\cdot \nabla K(x,y,t)] \qquad (1)$$

where *div* is the divergence operator, while ∇ is the gradient computed respect with the spatial variables.

Such equation can be discretized through a square lattice [3], with the the complex Crominance value K(x,y,t) associated to the vertices and the conductance coefficient c(x,y,t) associated to the arcs, (see Fig. 2), as follows:

$$\begin{aligned}[K_{i,j}]^{t+1} = [K_{i,j}]^t + \lambda[c_N\cdot\partial_N K_{i,j} + c_S\partial_S K_{i,j} + \\ + c_E\partial_E K_{i,j} + c_W\partial_W K_{i,j}]^t\end{aligned} \qquad (2)$$

where 0≤λ≤0.25 is required for the stability of the numeric scheme, N,S,E,W are symbols of the four vertices of the lattice and symbol δ defines the four differences *nearest-neighbour*:

$$\begin{aligned}\partial_N K_{i,j} &= (K_{i-1,j} - K_{i,j});\\ \partial_S K_{i,j} &= (K_{i+1,j} - K_{i,j});\\ \partial_E K_{i,j} &= (K_{i,j+1} - K_{i,j});\\ \partial_W K_{i,j} &= (K_{i,j-1} - K_{i,j});\end{aligned} \quad (3)$$

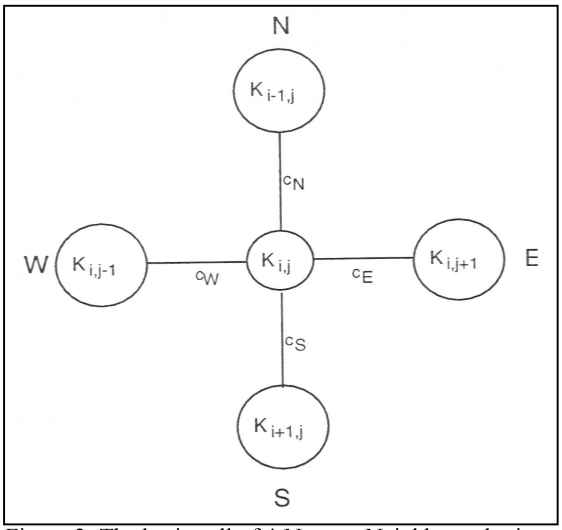

Figure 2: The basic cell of 4-Nearest-Neighbours lattice

The conductance coefficient is upgraded at each iteration as follows:

$$\begin{aligned}[c_N]^t_{i,j} &= g(|(\partial_N K_{i,j})^t|);\\ [c_S]^t_{i,j} &= g(|(\partial_S K_{i,j})^t|);\\ [c_E]^t_{i,j} &= g(|(\partial_E K_{i,j})^t|);\\ [c_W]^t_{i,j} &= g(|(\partial_W K_{i,j})^t|);\end{aligned} \quad (4)$$

The g(•) function can be modeled according to one of the following forms:

$$\begin{aligned}g(\nabla k) &= \exp(-(\|(\nabla k)\|)/A^2)\\ g(\nabla k) &= 1/(1+(\|(\nabla k)\|)/A^2)\end{aligned} \quad (5)$$

The first function is best suited to highlight edges provided with high contrast respect with the ones to low contrast, while the second form discriminates better between large and small regions. In this algorithm the second function has been chosen, in order to privilege the generation of large regions on the image, while the A costant value is dinamically computed for each iteration and set as 5% of maximum value of |(δK)|.

Finally, the image segmentation is obtained by separately partitioning of Crominance $K_d(x,y,t)$ and Lightness $L_d^*(x,y,t)$ and then combining the results through the *k-means* algorithm.
Given these settings, the proposed algorithm, based on anisotropic diffusion, becomes easy to be implemented, featuring a local behavior, i.e. the amount and the kind of smoothing are locally determined by the values of complex crominance and are adopted for each image region.
The choice for values of parameters T_1 and T_2 plays a major role in the setup of clustering process. The first, T_1, determines the average distance among the clusters, while the second, T_2, refers to to the average radius of a single cluster, if considered as a circle, and it is not possible to fix an *a-priori* value suitable for all images. Anyway an estimate of T_1 can be obtained from data distribution, estimating the radius of circle ρ_ω, in which a certain percentage of the data (ω = 95%) are contained.
Tests peformed on remote sensed images showed that setting $T_1=\rho_\omega/2$ and $T_2=\rho_\omega/4$ leads to excellent results on a large set of images and, in the same time, provides a limited number of segments (often less than 7), which well represent the color information of the image. Parameter T_2 can be freely set, provided that $T_2 < T_1$ in order to avoid the overlapping of clusters.

4. TEST AND RESULTS

In this section some examples of the application of the segmentation algorithm are reported. The remote sensed data were acquired by the Landsat-TM satellite on 12/26/1996 and on 05/03/1997. In the first phase, satellite images were processed using the classical approach, working on three data typologies: "natural color" images, infrared pseudocolor images and enhanced pseudocolor images.
The first class provides the user with photographic likewise viewing of the terrain, similar to color airphotos, while the second allows to get a more in depth analysis, discriminating between different categories of the same object class. For instance it is possible to detect different forms of vegetation, since the reflectance changes are strongly related with the morphologic structure of the leaf. Enhanced pseudocolor images are obtained by combination of different bands and can be useful employed to detect the soil humidity, urban and cultivated areas, and so on.
Figure 3a shows a Landsat-TM "natural" image taken during spring 1997, as result of application of RGB flter to TM1, TM2 and TM3 bands. Figure 4a shows a view of Porto Baseleghe lagoon (Venice, Northern Italy) by the mouth of Lemene river, which was taken during winter 1996. In this case the spectral components of the image were enhanced through following bands combinations: band TM7/5, where TM7/5=(TM7-TM5)/(TM7+TM5), band TM/6 as (TM7-TM6)/(TM7+TM6) and finally band TM3/1 as (TM3-TM1)/(TM3+TM1). The first band enhances the reflectance changes due to humidity and soil composition, the second discriminates between vegetation and urban areas, while the last band allows to distinguish between damp or dry soils, on the ground of their composition (organic material, kind of rocks).
Results of application of segmentation algorithm to these images are showed in figures 3b and 4b, in which clusters were early depicted in pseudocolors but in this paper have to be converted them in gray scale. Though it is not easy to appreciate by eye the performance of the algorithm, the results can be summarized as follows. Referring to Figure 3, the segmentation of this image allowed to discriminate perfectly between the wood area (in red in the resulting segmented color image) and cultivated and dry soils (respectively in green and blue), as

reported in Figure 3b. As regards the Figure 4b, it shows how well urban areas, the sea and vegetation areas could be segmented in comparison with corresponding image of Figure 4a.

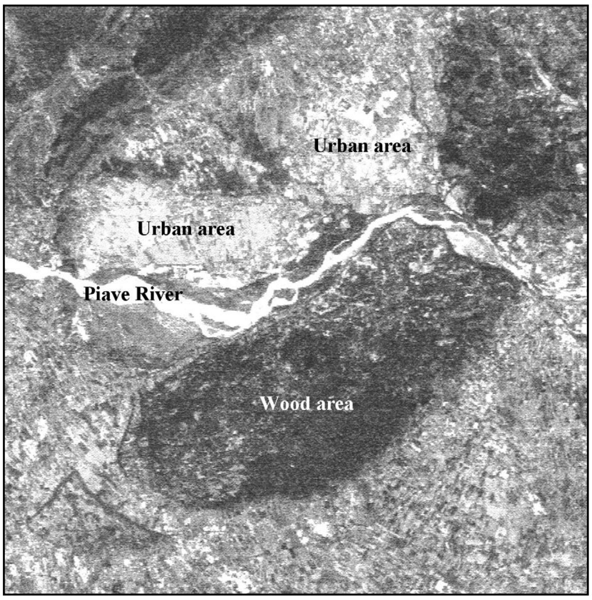

Figure 3a : Natural color image

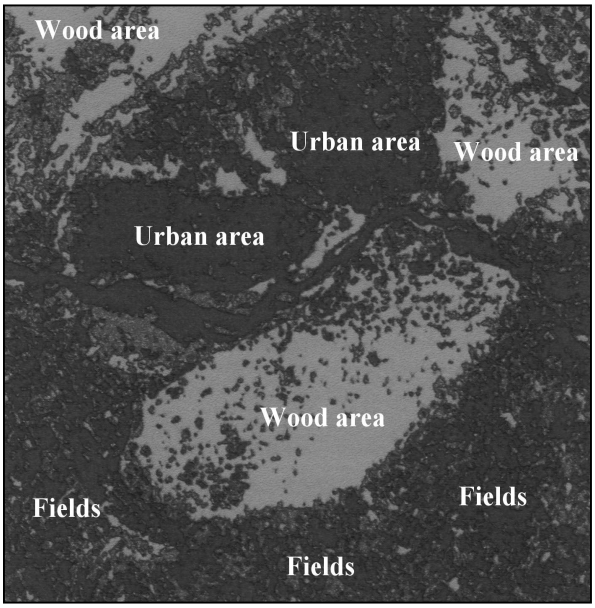

Figure 3b : Segmented natural color image

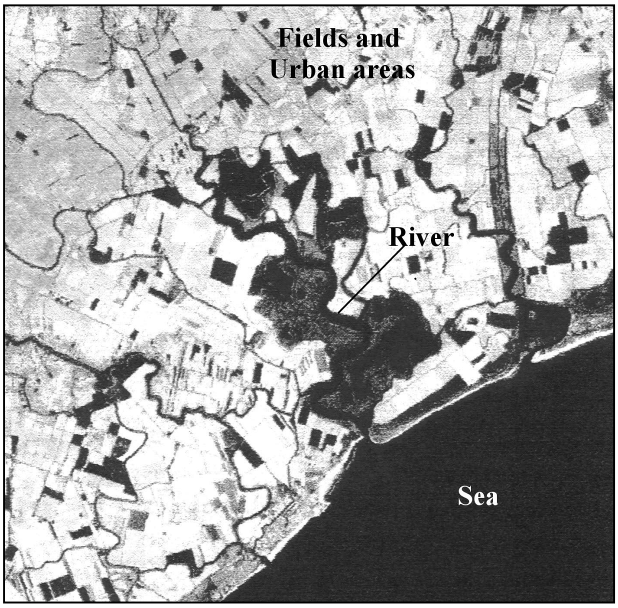

Figure 4a : Enhanced pseudocolor image of Porto Baseleghe

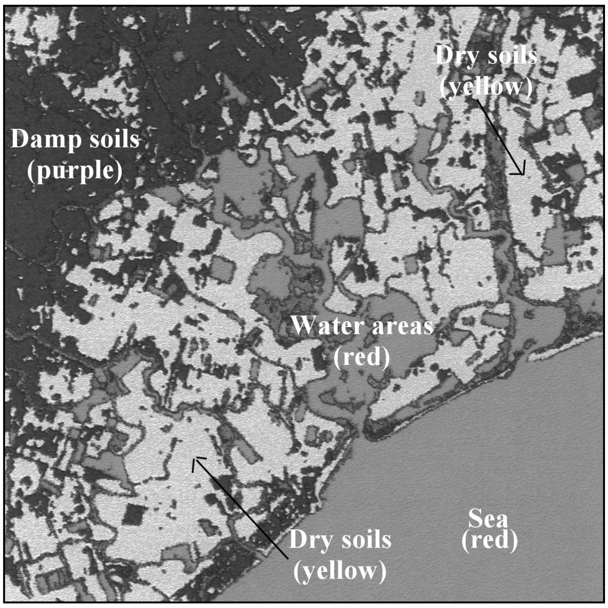

Figure 4b : Segmented image of Porto Baseleghe

5. CONCLUSIONS

In this work a combined method for remote sensed color images segmentation was presented. The method is based on the clustering and histogram thresholding technique, early developed in the field of Computer Vision for image processing. In this case the proposed algorithm was introduced as a second step in the tipical workflow of satellite image analysis in order to improve both the classification results of "classical" approach and the georeferencing of detected thematic areas. The advantage of proposed method relies in the fact that it is "unsupervised", i.e. it doesn't require any external human control or a-priori information. Therefore the procedure can be fully automated and can be easily implemented in any GIS application.

Performance of the algorithm were assessed by comparison between the results of "classical" Remote Sensing image analysis with the ones of the presented method, which were applied to the same set of satellite images. As showed in previous section, the segmentation algorithm could be successfully applied also to pseudocolor images, providing excellent results if the image is composed by wide and well defined regions. Unfortunately, if the satellite image is fragmented, and shows very similar colors distributed in a large amount of small regions, the segmentation algorithm provides often an ambiguous and unsatisfactory result.

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REFERENCES

[1] Lucchese L., Mitra S.K., . 1998. An algorithm for unsupervised color images segmentation. *Proc. of 1998 IEEE 2nd Workshop on multimedia signal processing*, Redondo Beach, CA, USA, pp. 33-38.

[2] Lucchese L., Mitra s.K., 1999. Unsupervised segmentation of color images based on k-means clustering in the chromaticity plane. *Proc. of IEEE Workshop on content-based access of images and video libraries (CBAIVL '99)*, Fort Collins, CO, USA.

[3] Perona P., Malik J., 1990. Scale space and edge detection using anisotropic diffusion. *IEEE Trans. on PAMI*, Vol 12, No 7, pp 629-639, July 1990.