Our world from above: texture based segmentation for landscape analysis

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Abstract. Evaluation of aerial pictures is of key importance for environmental analysis given the large extensions of land to study. This paper focuses on texture based segmentation of aerial images and characterisation of landscapes. Characterisation is achieved by means of a histogram of microtexture LBP/C vectors. Segmentations is hierarchically performed in a top down way by comparing the textures of potentially similar regions by metric G. The algorithm has been succesfully tested for a variety of pictures presenting different sizes and textures.

1 Introduction

Internet was originally established as a way for researchers to share data across geographical boundaries. Nowadays, Internet as well as a variety of ICTs are being used to share information about our complex global environment so that societies learn how to protect the earth's fragile environment. This approach is known as e-environment [8]. One of the main goals of e-environment is to make data from a variety of resources easy to collect, distribute and analyse to allow environmental awareness. Naturally, ICTs cannot stop environmental degradation: to be effective, they must be accompanied by an international commitment to globally avoid further degradation of the environment. Nevertheless, e-environment is of extreme importance not only for scientists, but also for global policy-makers so that they can better address problems through environmentally friendly collective action [6].

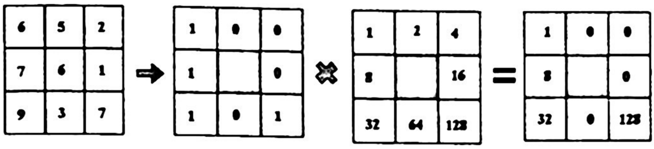
Currently, much effort on e-environment is focused on data gathering on different areas, like wetland, alpine or forest areas, evaluation of soil erosion and desertification or monitorization of urban growth [4]. Since observation in this cases is bound to be performed at large scale, it typically relies on aerial or satellite pictures. Land digital analysis is usually associated to GIS (Geographical Information Systems), which links geographic information with descriptive information. GIS can be used to deal with natural resources more efficiently in many applications ranging from managing facilities to understanding global climate changes [5].

GIS are already in use for decision making all around the world. In Norway, GIS are being used to find new sites for stores. In Germany, GIS are assessing markets for new commercial activities. In Ecuador, automated maps are being used to show where milk delivery trucks go, saving millions of dollars in logistical costs. In Florida, Power and Light is using GIS to track weather fronts and hurricanes. GIS are under use to evaluate farming and typical crops in different parts of Africa. In Canada, Timberline Inc. is looking at sustainable forests and the visual and biological impact of forestry by means of GIS. In New Zealand, GIS are being used to automatically generate aeronautical navigation charts. The Bangladesh Agricultural Research Council uses GIS to analyse crops in the landscape. GIS are also being used to study the effects of global warming, using maps to study the sea level rise inundation occurring off the coast of Delaware and the melt of glaciers in the Himalayas. It can be noted that GIS allow exploitation of different knowledge resources and, consequently, provide an important instance to decision support systems for hazard identification, risk assessment or evaluation, intervention and decision-making [2].

The National Imagery and Mapping Agency, the largest provider of geographic data in the world, is building databases, automating its charts and mapmaking process, and distributing these charts around the world to its users and customers. Specifically, analysis of landcover and the monitoring of environmental changes of agricultural and urban areas by image classification is one of the major application of remotely sensed images [10]. However, given the large amount of raw data available, automatic non supervised image analysis tools are necessary. One of the most important low level processing tools is segmentation, which basically consists of dividing a given image in homogeneous regions. Naturally, segmentation is necessary to divide an image into areas presenting different crops, forests, urbanized areas, etc. After an image is segmented, the size and nature of the different regions inside can be estimated. However, segmentation of these images is not simple, because differences between coexisting areas in a picture can be subtle [3]. Some works rely on supervised segmentation by direct human observation [10] and focus on refinement. In other cases, neural networks are used to recognize previously learnt patterns in the images [17]. Multispectral analysis has also been used to extract relevant information from spectra [9]. Principal Components Analysis has been used in a similar way [1]. In this paper we present a texture based image segmentation tool to separate aerial or satellite views into homogeneous regions. Its main advantage is that it works at different spatial scales and allows simple characterisation of previously unknown land areas. First, texture is defined in section 2, where it is explained how it is characterised. Section 3 focuses on the segmentation algorithm, which has been designed in a hierarchical way to efficiently cope with large images. Section 4 presents several experiments and results. Finally, conclusions and future work are presented in section 5.

2 Texture Characterization

Texture can be defined as a structure consisting of a large number of more or less ordered similar elements or patterns without any one of these drawing special attention [16]. In order to be digitally processed, texture needs to be analytically defined. There are many texture measures, mostly adapted to the problem at hand.



LBP = 1+8+32+128 = 169

Fig. 1. Calculation of LBP

Ojala and Pietikainen compared different options in [11] and finally proposed to use Local binary patterns (LBP), a simple yet effective texture analysis technique. In LBP each pixel is assigned a certain index according to the structure of its surrounding pixels. Fig. 1 shows an example of how an LBP is calculated for a pixel:

1. The 8-neighbourhood of the studied pixel is thresholded with respect to the pixel value. Pixels lower than the studied one become equal to 0 and the rest become equal to 1.
2. The thresholded neighbourhood is multiplied by a mask composed of a set of constants which are the first 8 power of two (1,2,4,8,16,32,64 and 128).
3. The resulting values are added to obtain the LBP of the central pixel.

It has been reported that contrast is also of key importance regarding textures: a pattern in black is not equal to the same pattern in white. Hence, an additional contrast measure (C) is added to the pixel texture. C is calculated as illustrated in Fig. 2. A mask of 0s and 1s is applied to the 8 neighbourhood of the evaluated pixel. Pixels related to 0s and 1s are added and averaged separately and then their difference is calculated. The whole range of possible values is discretized into N bins and C is equal to the bin the value belongs to.

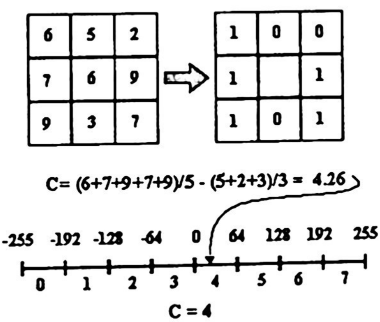
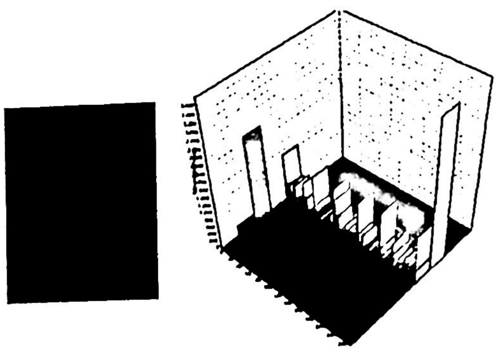


Fig. 2. Calculation of C

It is also important to take into account that texture, by definition, is related to large areas rather than to a single pixel. Texture at pixel level as previously defined is known as microtexture, whereas texture at large scale is known as macrotexture. A common and simple tool to represent the distribution of a given magnitude over a large number of points is its histogram [12][14]. In this case, to represent LBP/C over a given pixel area, a 3D histogram is required, where two axes represent all LBP and C values, respectively, and the third one represents the number of points presenting any given LBP/C value. The histogram, consequently, has $256xN$ bins.



(a) (b)

Fig. 3. Macrotexture: a) textured area; b) LBP/C histogram

3 Homogeneity Criterium and Hierarchical Segmentation

Unsupervised segmentation of textured images is a difficult and challenging low level vision problem that roughly consists of partitioning an image into homogeneous regions. Most segmentation techniques can be roughly divided into: i) measurement space-based algorithms; ii) pixel similarity based algorithms; iii) pixel difference based algorithms; and iv) physics based schemes. Measurement space-based algorithms, like histogram thresholding or clustering methods, are simple and fast but they usually do not take into account spatial context information until postprocessing stages. Both pixel similarity based algorithms, like region growing and *split and merge* methods, and pixel difference based algorithms, like contour detection, take advantage of the pixel context interaction but they are typically computationally expensive. To take advantage of spatial context but also keep a bounded computational complexity, some methods rely on hierachical image processing [7][13]. In this paper we propose a hierarchical split and merge segmentation process based on a 3D structure that we call uncomplete pyramid. The process relies on pruning an ordinary pyramid like the one in [15] until all its nodes are homogeneous. A typical approach to homogeneity is similarity evaluation: if two regions are similar, the region resulting from merging them both is homogeneous. Since textures are defined by means of histograms, it is necessary to use a special metrics to compare two of them. In this case, we use G to compare LBP/C histograms, as defined in the following equation:

$$G = 2([\sum_{A,B}\sum_{i=1}^{N} f_i log f_i] - [\sum_{A,B}(\sum_{i=1}^{N} f_i) log(\sum_{i=1}^{N} f_i)] -$$

$$[\sum_{i=1}^{N}(\sum_{A,B} f_i) log(\sum_{A,B} f_i)] + [(\sum_{A,B}\sum_{i=1}^{N} f_i) log(\sum_{A,B}\sum_{i=1}^{N} f_i)]) \qquad (1)$$

A and B being histograms, N being the number of points of the histogram and f_i being the frequency of element i.

In order to segment our textured image, first a linked pyramid is built. A linked pyramid is a graph $G(V, E)$ consisting of a set of vertices V linked by a set of edges E. We refer to the vertices as nodes and to the edges as links. The base of the pyramid is designated as level 0. Each node n in a pyramid is identified by (l, i, j) where l represents the level and (i, j) are the (x, y) coordinates within the level. We use a 4-to-1 linked pyramid, where each level is generated by reducing the resolution of the previous one by a factor of 4. Thus, the color of a node (l, i, j) (parent) is calculated as the average of the four nodes inmediately below at level $l-1$ (children). We associate several parameters to each node:

- Homogeneity: $H(l, i, j)$ is set to 1 if (l, i, j) is homogeneous. Otherwise, it is set to 0.
- Texture: $T(l, i, j)$ is equal to the combined LBP/C histogram of the children of (l, i, j).
- Parent link: $(X, Y)_{(l,i,j)}$. The values of parent link of the children of (l, i, j) are initially set to (i, j).

Once the structure is completely built, non homogeneous nodes are pruned as follows:

- *Split*. Starting at the top level, for each node (l, i, j) check if G is lower than a threshold Th for every two of its four children. If this condition is true, set $H(x, y, l)$ to 1, otherwise set $H(x, y, l)$ to 0. When this step is accomplished for the whole structure, remove all nodes presenting an homogeneity value equal to 0. When nodes are removed, their children become orphan nodes. The parent links of all orphan nodes are set to $NULL$. Orphan nodes of the resulting uncomplete pyramid are linked to homogeneous regions at the base, but the resulting partition is clearly suboptimal and strongly depend on the image layout.
- *Merge*: Starting at the top level, for each orphan node (l, i, j):
  1. Parent search: link to parent $(x'_p, y'_p, l+1)$ of a neighbour node (x', y', l) if the following conditions are true:

- $H(x, y, l) = 1$ & $H(x'_p, y'_p, l+1) = 1$
- $G[(x, y, l), (x'_p, y'_p, l+1)] < Th$
- $G[((x, y, l), (x', y', l)] < Th$

If there are several candidate parents, link to the spatially closest one.

2. Intralevel twining. Link to a neighbour node at the same level, (x', y', l) if the following conditions are true:
   - $(X, Y)_{(x', y', l)} = NULL$
   - $H(x, y, l) = 1$ & $H(x', y', l) = 1$
   - $G[(x, y, l), (x', y', l)] < Th$

Since texture at pixel level is not significant, the merge process does not continue to the base of the structure, but stops in an upper level, usually, level 2 or 3. When this process finishes, each orphan node in the pyramid is linked to an homogeneous texture region in the base, which is characterized by its LBP/C histogram and, hence, can be identified and measured. Fig. 4 shows a simple example of this technique. Assuming that black nodes have a texture and white nodes have a different one, there are only two levels in the pyramid of the example (Fig. 4.a), because level 2 would have no nodes. First, there is an intralevel twinning stage at level 1 (Fig. 4.b). Then, nodes at level 0 having a nearby parent link to that parent (Fig. 4.c). After that, nodes at level 0 having a non-orphan sibling link to its parent (Fig. 4.d). Finally, there is an intralevel twinning stage at level 1 (Fig. 4.e). The resulting regions are presented in Fig. 4.f. It is interesting to note that some adjacent regions presenting the same texture, like the white ones, are not finally merged into a single region because of the sequentiality of the process. A final merging process at the base can solve this problem.

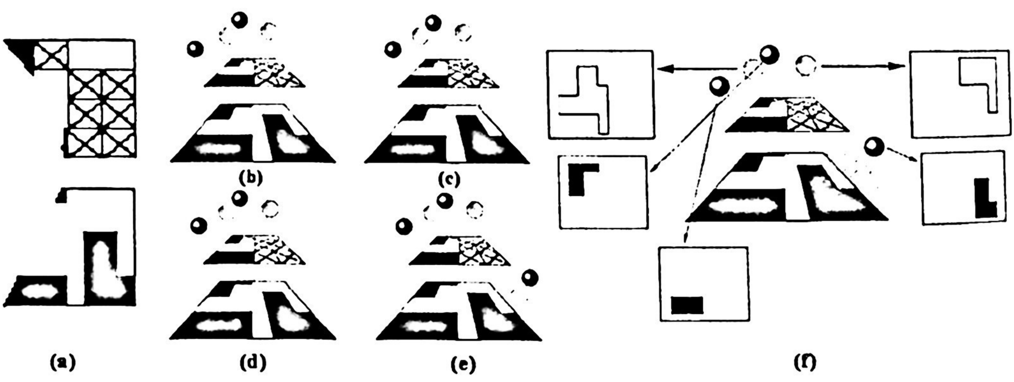


Fig. 4. Hierarchical segmentation: a) levels 0 and 1 of the pyramid; b) intralevel twining at level 1; c) parent search at level 0; d) intralevel twining at level 0 (step 1); e) intralevel twining at level 0 (step 2); f) resulting regions

Fig. 5 shows an example of the proposed segmentation technique at different stages over a Mexico DF aerial image. Fig. 5.a shows the image after the split stage. It can be observed that despite the different grays in the city buildings, textures within each square are roughly homogeneous. Fig. 5.b shows the same image after parent merging. Regions are not square anymore. It can be observed that, despite their differences, city areas and park areas start to be defined. Fig. 5.c shows the picture after intralevel twinning. The park area is divided into two regions because of the lake and the white building in the center, but it is adequately separated from the buildings. A final merging process could correct this, as aforementioned. Buildings are mostly separated according to their proximity to the camera, because texture is not scale independent but it can be appreciated at plain view that the separation is mostly correct.

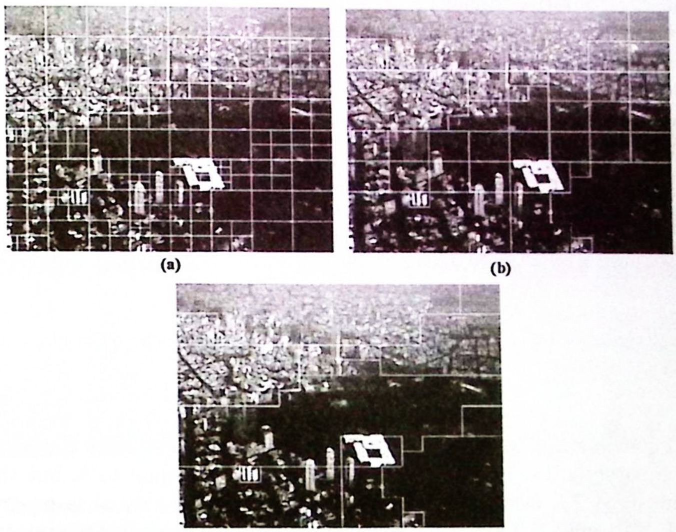


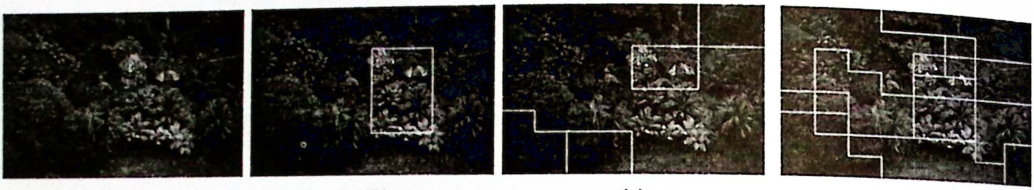
Fig. 5. Example of hierarchical segmentation at the base of the pyramid: a) image after split; b) image after parent linkage; c) image after intralevel merging

4 Experiments and Results

The proposed algorithm has been tested on an ordinary Pentium PC 800 with 256 Mb RAM under Windows 98. As aforementioned, there are many sites with aerial and satellite pictures available in Internet. Specifically, pictures in this paper have been downloaded from TerraServer USA [1], Airfoto [2] e Inmonetwork [3]. All pictures present different resolutions, have been captured at different heights and have been processed in greyscale.

A first problem with segmentation algorithms is how to correctly fix their working parameters. Specifically, the proposed algorithm has two important parameters: N, the number of contrast bins and Th, the similarity threshold to assume that two regions conform an homogeneous one. The effect of these parameters on segmentation can be appreciated in Figs. 6 and 7.

Fig. 6.a presents a 400x267 aerial view of a couple of huts in the Costa Rica jungle, which can be segmented in approximately 1.6 s. Figs. 6.b-d show the segmentation results for a contrast quantization N of 4, 8 and 16 bins. Naturally, when the number of bins is small, less contrast differences can be appreciated and the resulting number of regions is small as well. In the case in Fig. 6.b, for $N = 4$, only the huts can be separated from the jungle. When the number of bins is increased, more regions start to appear. In N is too large (Fig. 6.d), small contrast differences avoid fusions and resulting classes are no longer correct.



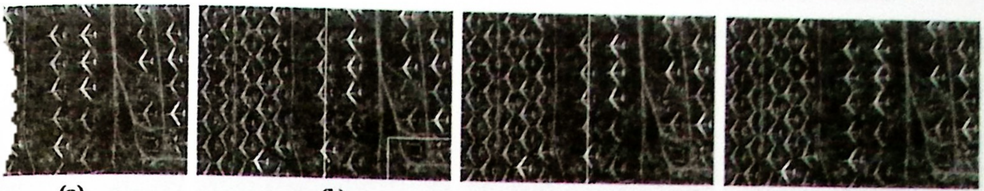
(a) **(b)** **(c)** **(d)**

Fig. 6. Segmentation of a jungle image for different C partitions: a) original image; b) N=4; c) N=8; e) N=16

Fig. 7.a shows a 600x400 image of an airfield in Tucson, which is segmented in approximately 2.2 s. In this case, N is constant and equal to 8, but the value of the threshold Th used to determine if two regions are equal is progressively increased. Naturally, if Th is too low, minor differences provoke the appearance of small classes (Fig. 7.b). Using a threshold equal to 400, the image is halved into regions with more or less plane density (Fig. 7.c). Using a threshold equal to 600, the whole image is detected as an unique region.

It can be appreciated that parameters do have an important effect on segmentation results. However, it can also be appreciated that rough variations in these parameters are allowed and that segmentation results are nevertheless reasonable from an observer's point of view. Basically, in order to choose a set of parameters, it is important to know the application to be implemented. If small differences need to be appreciated, Th must be low and N must be high. If regions need to

[1] $http://www.terraserver.microsoft.com/$
[2] $http://www.airphotona.com/index.asp$
[3] $http://209.15.138.224/inmonacional/mapas.htm$

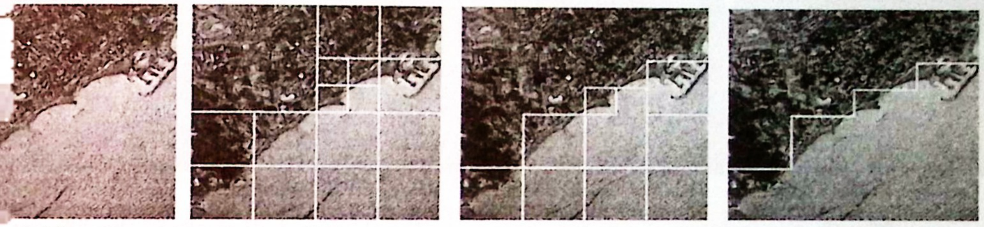


(a) (b) (c) (d)

Fig. 7. Segmentation of an airfield image for different values of threshold Th: a) original image; b) Th=250; c) Th=400; e) Th=600

be large, Th should be high and N should be low. In the following experiments, different pictures are processed for Th equal to 600 and N equal to 8. These images present different sizes so that the effect of size on processing time can be appreciated.

Fig. 8 present an aerial 256x256 picture of Benalmadena (Spain). It was processed in 0.8s. It can be appreciated that the urbanized area is correctly grouped together into a single region, which is clearly separated from the sea. Naturally, the shape of the regions is rough because, as aforementioned, textures are not analyzed at the highest resolution level. This means that the smallest square that can be defined is as large as $2^L x 2^L$ pixels, L being the last processed level.



(a) (b) (c) (d)

Fig. 8. Segmentation of a coast image: a) original image; b-d) results at the different stages of the process

Fig. 9 present a 416x368 crop aerial picture in Andalusia (Spain), segmented in 2 s. It can be observed that crops are adequately separated into regions, roughly corresponding to their nature. It can be appreciated, though, that there are some segmentation problems in region boundaries. These problems are typical in segmentation of real images and they appear because no texture is clearly defined at region borders.

Fig. 10 shows a 600x423 picture of Barcelona port (Spain), which was segmented in 3.9 s. It can be observed that the parking is correctly separated from the sea and the nearby buildings, even though there is a segmentation error in the

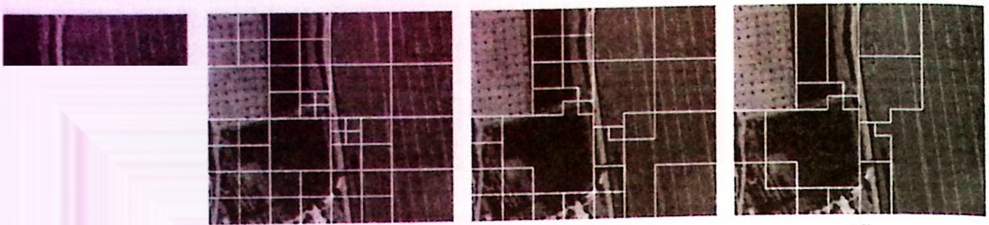


Fig. 9. Segmentation of a crop image: a) original image; b-d) results at the different stages of the process

top right corner of the image. In this region, the sea is merged with land. This occurs because during the parent search stage (Fig. 10.b), the sea child nodes link themselves to the top right parent, which has a portion of sea. However, since the parent also has a portion of land, the other two nodes link to it as well. The problem would have been solved if such parent had not existed, but since it was located over a boundary, homogeneity was not clearly defined in the node.

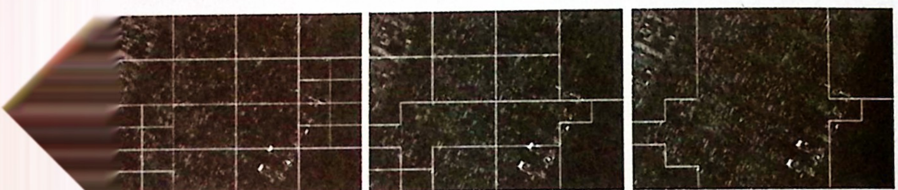


Fig. 10. Segmentation of a parking image: a) original image; b-d) results at the different stages of the process

Fig. 11 shows a 1024x768 aerial view of the Palacio Real in Madrid. It was segmented in 11 s. It can be appreciated that the park and the gardens are correctly separated from the building areas, which are divided into two regions depending on the layout of the existing buildings. Again, in this case, the boundaries between the regions on the right of Fig. 11.d provoke a segmentation error.

Finally, it is important to note that, after segmentation, every region is characterised by an LBP/C histogram and, hence, next time a similar region is detected, it can be identified by comparing its LBP/C histogram with the known one using G. Thus, different crops, landscapes and areas can be correctly recognized in a segmented image.

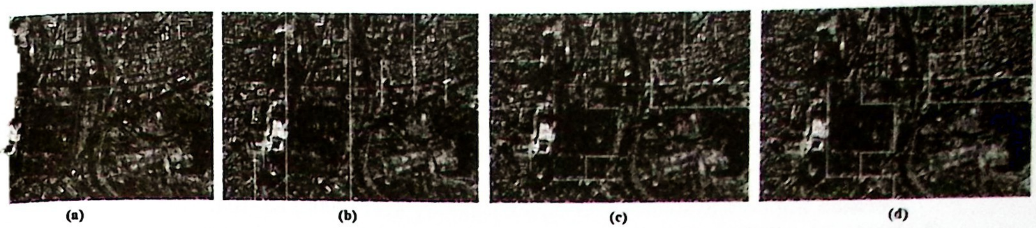


Fig. 11. Segmentation of an urban image: a) original image; b-d) results at the different stages of the process

5 Conclusions and Future Work

We have presented a hierarchical texture based segmentation algorithm for aer images. This algorithm relies on representing the texture of a given area by mea of an LBP/C histogram, which is also used to recognize known textures in othe images and, thus, identify different landscapes. Histograms are compared by mean of the G metric. The hierarchical nature of the process improves the speed of se mentation even in ordinary, non dedicated processors. The system depends two parameters: the maximum contrast difference allowed within an homogeneo region and the maximum histogram difference to assume that two adjacent gions belong to the same larger one. The value of these parameters has influen on segmentation results, but they do not need fine-tuned and, depending on th application, a suitable set can be easily chosen.

Future work will focus on including color textures, to add information to th current data structure. Also, it is necessary to improve tecture characterizatio to avoid handling large histograms by dimensionality reduction. Finally, it wou be desirable to add high level intelligence to the system so that parameters adap unsupervisedly to the processed image for best results.

Acknowledgments

This work has been partially supported by the Spanish Ministerio de Ciencia y Tecnologia (MCYT) and FEDER funds, project No. TIC2001-1758.

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