AUTOMATIC EXTRACTION OF PHYSIOGRAPHIC FEATURES AND ALLUVIAL FANS IN NEVADA, USA FROM DIGITAL ELEVATION MODELS AND SATELLITE IMAGERY THROUGH MULTIRESOLUTION SEGMENTATION AND OBJECT-ORIENTED CLASSIFICATION

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ABSTRACT

There is a need to automate terrain feature mapping so that to make the process more objective and less time consuming by using proper feature extraction techniques. The objective of this study was the use of object-oriented image analysis methods for the automatic extraction of physiographic regions and alluvial fan landform units. The study area was located in Nevada, USA. The data used included an ASTER L1 satellite image, the 1^{o} Digital Elevation Model and the GTOPO30 Digital Elevation Model, available by USGS. At first, a multiresolution segmentation algorithm was applied for extracting image primitives. A class hierarchy was defined in order to classify these primitives into semantic image objects. A fuzzy classification then provided the first approximations of three physiographic feature types (*basins*, *piedmont slopes* and *mountains*). Further processing, by a segment fusion technique, resulted in the reclassification of these image semantics into the final physiographic feature units. For the extraction of alluvial fan units, a multiresolution segmentation technique was developed, delivering object primitives at several resolution levels. At the finest level, the physiographic feature types were extracted from the DEM. At a medium level, a knowledge base including definitions of *Alluvial Materials*, *Sediments*, *Basin Materials* and *Rock-Mountain Materials* was implemented. This level was classified through several iterations, using spectral information for the first iteration of the classification procedure and heuristics concerning contextual information for the second iteration. Finally, at the coarse level, a projection was made, classifying the data into two classes: *Alluvial Fans* and *Other Objects*. The results were compared to manually produced maps by an expert geomorphologist and to computer-produced maps and they were found satisfactory.

INTRODUCTION

In recent years, research has progressed in computer vision methods applied to remotely sensed images such as segmentation, object oriented and knowledge-based methods for classification of high-resolution imagery (Argialas and Harlow 1990, Kanellopoulos et al. 1997). In Computer Vision, image analysis is considered in three levels: low, medium and high (Argialas and Harlow 1990). Such approaches were implemented usually in separate software environments since low and medium level algorithms are procedural in nature, while high level is inferential and thus for the first one needs procedural languages while for the second an expert system environment is more appropriate. Only very recently however, a new methodology called Object Oriented Image Analysis was introduced, integrating low-level, knowledge-free segmentation with high-level, knowledge-based fuzzy classification methods. This new methodology was implemented through a commercial software, eCognition, which was made available with an object-oriented environment, for the classification of satellite imagery (Baatz and Shape 2000, Benz et al. 2004).

In the past, research has been done in building knowledge bases for the interpretation of landforms and in methods for automatic landform extraction from Digital Elevation Models and satellite images (Argialas and Miliaresis 1997, Miliaresis and Argialas 1999). It is not possible to separate the mountain ranges from the basins and piedmonts by thresholding the Digital Elevation Model (DEM) (Miliaresis and Argialas 1999). Therefore a segmentation procedure was required to define the mountain ranges and basins from a DEM. Miliaresis and Argialas (1999) developed segmentation methods for geomorphological feature extraction from the GTOPO30 digital elevation model (DEM). At first, the gradient and the orientation were computed from the DEM, then, runoff simulation was used for determining the drainage network and the divides (mountain ridges). The points of the drainage network and the divides were used as seed points for region growing segmentation of the DEM into mountain ranges and basins, based on the slope gradient values. The area between these two types of regions was defined as piedmont slope. Also, work has been done for automatic extraction of Alluvial Fans from DEM and satellite images (Miliaresis and Argialas 2000). The study area was part of the Basin and Range Province and in particular the Death Valley region in Nevada, USA.

The objective of this paper was the use of object oriented image analysis techniques for the extraction of geomorphological terrain features from digital elevation models and a comparison to results achieved with previous methods. This research included the design of an object-oriented representation and a fuzzy knowledge base as part of a high level image processing step for the identification and delineation of geomorphologic features. Also, a main objective of this research was the investigation and implementation of object oriented image analysis algorithms and fuzzy logic techniques for the recognition and classification of alluvial fans based on their spectral, topographic, topologic, geometric and contextual knowledge from digital elevation models and multispectral satellite data. Alluvial fans are best developed in arid areas of high mountain ranges such as those of the Southwest United States where approximately 30 percent of the land are covered by alluvial fans. In arid regions, alluvial fans are ground water indicators and their soils provide good foundation conditions for highways and buildings (Way, 1978). Therefore, alluvial fan mapping is of significance to the remote sensing, geologic and civil engineering community.

DATA USED – STUDY AREA

The study area is part of the *Great Basin section* of the *Basin and Range Physiographic Province* and the Death Valley region in Nevada, USA. This region is characterized by large mountain ranges intervened by tectonic alluvial basins (Fenneman 1931, Peterson 1981). The data used was the GTOPO30 Digital Elevation Model available through the USGS with spacing of 30 arc seconds (Figure 1).

Data used also included the 1-degree Digital Elevation Model with 75m grid size, and an ASTER Level 1 satellite image with 14 channels available through USGS (EOS-DIS) (http://edcimswww.cr.usgs.gov/pub/imswelcome/) both for the Death Valley region, USA. The ASTER L1 dataset included 14 channels: channels 1-3, 15m resolution in the visible and near infrared region of the spectrum, channels 4-9, 30m resolution in the short-wave infrared region and channels 10-14, 90m resolution in the thermal infrared region.

On the ASTER L1 image the following land cover classes have been observed: alluvial fans (small and large), rocky mountains with absence of vegetation, bahadas, basin floor salt deposits, basin floor sediments and the road network (Figure 2).

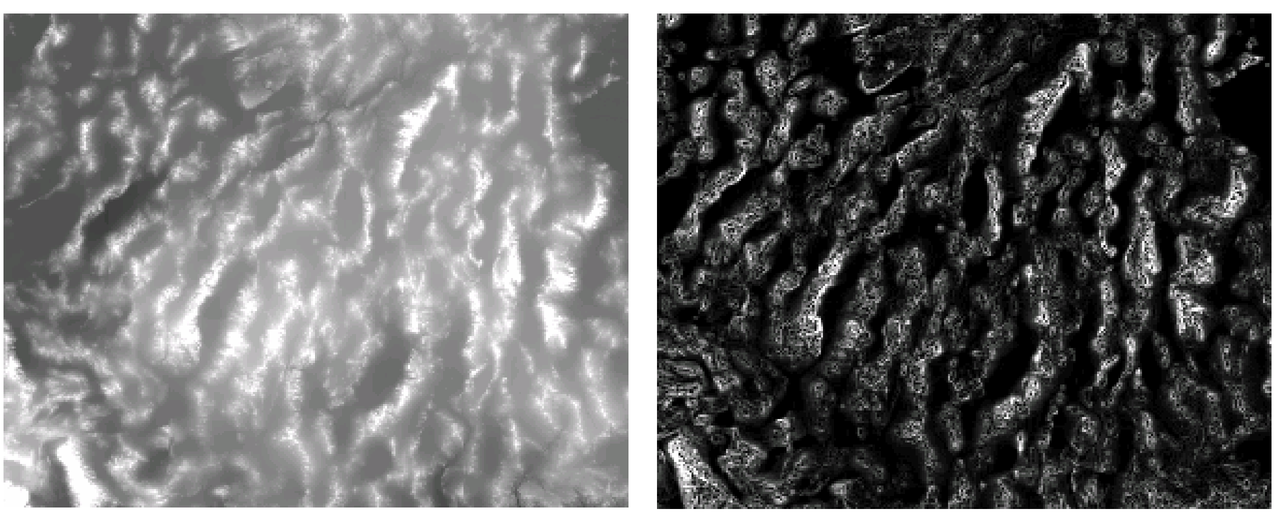


Figure 1. Left: The Digital Elevation Model GTOPO30 of the study area. Right: The slope gradient image computed from the DEM.

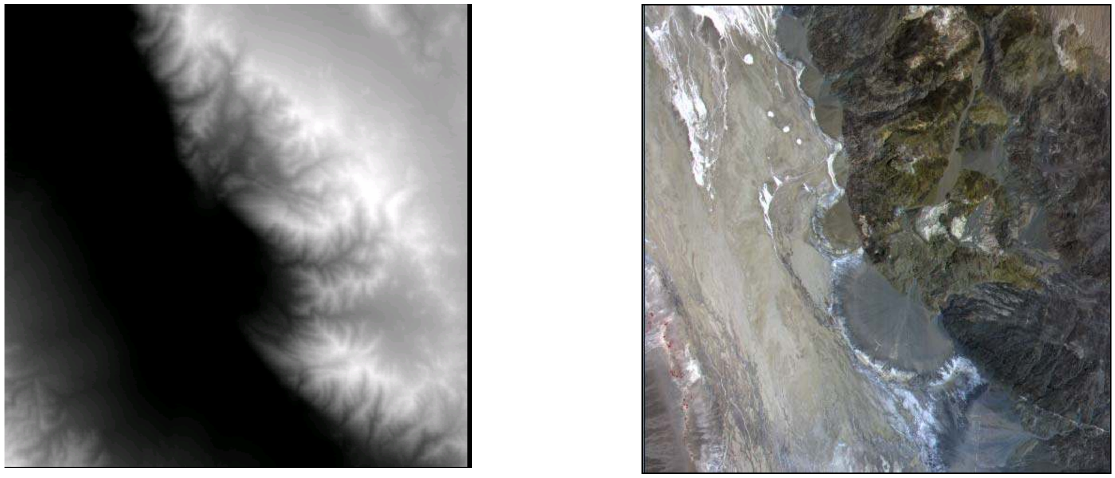


Figure 2. Left: The 1-degree DEM provided by USGS for Death Valley. Right: The ASTER L1 Dataset of Death Valley in RGB composite

METHODOLOGY

Segmentation of the GTOPO30 DEM Data

The segmentation procedure had the objective, to provide the primitive objects, in order to apply higher level knowledge in a later step and classify the primitives into semantic objects. Having a-priori knowledge of the heuristics to be used in later classification stages, it was of high importance to produce initial objects that would be appropriate for later steps. The later stages of classification were to use slope information in order to produce a first result and then to refine it. Thus, large size primitive objects, would not be the best choice in this case, in order to initialize classification. A large scale parameter would have the effect of large scale objects and coarse information for slope, as the means of slope information would be computed for each object. With smaller scale parameter, the segmentation algorithm was expected to provide smaller objects and those would keep a better initial representation for slope information. The basic idea was to merge the primitives in later stages using geomorphometric knowledge and production rules, rather than in a knowledge-free segmentation stage.

The segmentation parameters were determined through a trial and error procedure. Large (50) and medium (12) scale parameters were used for testing purposes, but were found unsatisfactory and were dropped out. Taking into account the a-priori higher level knowledge of the extraction problem and that basic aim of segmentation was the minimization of loss of information from the DEM, in order to make the maximum use of slope gradient information, it became evident that the desirable segment size must be reduced almost to the level of the grid spacing of the DEM. After several trials, a scale parameter of 3 was selected.

Regarding the parameters of *color* (elevation) and *shape*, since the *shape parameter* almost looses its meaning for very small size segments, it was given a small value (0.3) just in case some segments could grow to the degree to have a meaningful shape parameter. *Compactness* was set to 0.5, *smoothness* to 0.5, while *color* was set to 0.7. Figure 3 shows the final segmentation of GTOPO30 in magnification to make evident the size of the primitive objects which on the average did not exceed the size of the grid spacing of the GTOPO30.

Knowledge Based Extraction of Geomorphological Features

Following the implementation of the segmentation, the obtained primitive objects must be classified into specific terrain classes. The first step of classification is the determination of classes, their features, and their hierarchical structure. The desired terrain objects are mountains (most of these are mountain ranges), basins, and piedmont slopes.

Given that a proper segmentation – delivering optimal terrain objects – was difficult to be achieved based on the tested homogeneity criteria and that the best segmentation resulted into very small primitive segments of minimal semantic meaning, there was a need to also build a knowledge base as a method of terrain object extraction. The knowledge base should work on the classification of object primitives provided by the segmentation algorithm, not based on a homogeneity criterion, but instead on merging heterogeneous class segments into super objects representing the desirable terrain classes. For this procedure, the *classification-based segmentation* feature was used. The formulation of knowledge-based rules for the so-called *classification-based segmentation* or *object fusion* was carried out by defining structure groups. A *structure group* was defined as a collection of classes representing the same structure in an image and consisted of classes defined for different levels in the terrain object hierarchy. The basic principle is that a sub-object (such as the "noise" within a mountain object) which was assigned to a class (such as the piedmont slope class) other than the class of its super-object (mountain class) is treated as heterogeneous or as "not belonging" to this super object. Object fusion aims at the regrouping of this sub-object (piedmont slopes segment) to the proper super-object (mountain object).

In the following, each class will be re-defined through an iterative approach in three stages. Through each iterative stage, the previously classified terrain objects will be reclassified, regrouped, or refined through knowledge-based procedures involving redefinition of the terrain classes, so that to better determine the desirable terrain objects at each stage. Due to the iterative redefinition of each class, at each level of the process, a symbol after the name of each class will be used to define the *level* at which the class was defined, e.g. *mountains (L1)* for mountains of Level 1. Each class was described by a set of features. *Feature selection* was carried out by taking into account the a priori known attributes of the classes (Fenneman 1931, Peterson 1981) and inspection of the statistical properties of the objects.

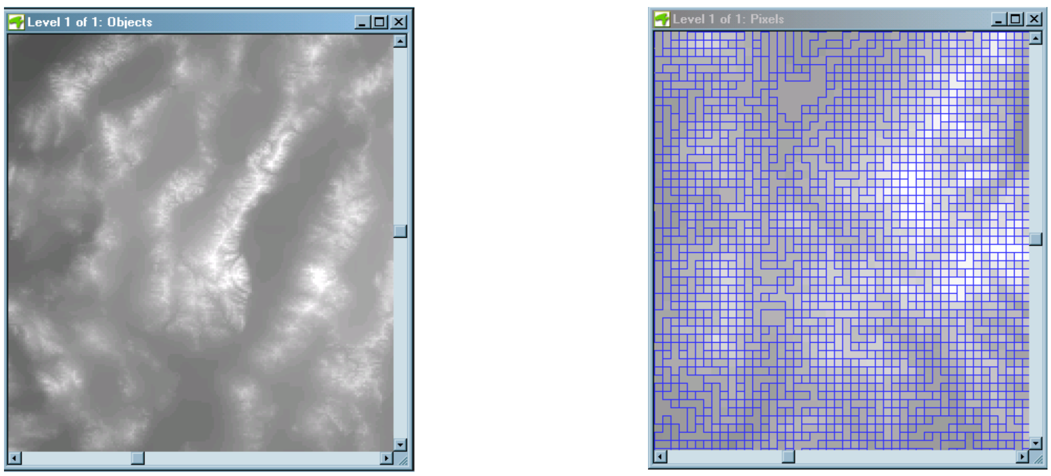


Figure 3. Left: Zoom-in view of the GTOPO30 DEM. Right: The final segmentation result with scale parameter 3.

At the first stage, the following terrain classes were defined

a) *Mountains like (L1)* aiming at defining terrain objects which correspond to mountain ranges,
b) *Basins like (L1)* aiming at defining objects which correspond to basins, and
c) *Piedmont slopes like (L1)* aiming at defining objects corresponding to piedmont slopes.

At this stage, these classes were defined based on their slope gradient. Miliaresis and Argialas (1999) in their approach of region growing segmentation used two slope gradient thresholds. In the present approach, those two thresholds were used as first approximations for defining fuzzy membership functions for the slope gradient to discriminate the mountains from the basins. The initial *mountains like (L1)* class constraint was: slope gradient > 6 and the initial *basins like (L1)* class constraint was: slope gradient <2.5. However, the slope gradient constraints were converted to fuzzy membership functions. The *piedmont slopes like (L1)* class was defined as the complementary fuzzy membership function of the above two functions for the *mountains like (L1)* and *basins like (L1)* objects.

Following the feature definition for each of the terrain classes, classification of the segments took place. The results of this first stage classification are shown in Figure 4a. An implementation of *object fusion* resulted into grouping of neighboring initial object primitives into larger objects.

The basic aim of the second stage was to identify which *mountains like (L1)* objects were correctly classified and which were not, since the subsequent knowledge based procedures should take into account spatial neighborhood relations between the extracted mountain objects. To check the status of the classified mountains, a constraint was applied using a fuzzy membership function: if the minimum area of a *mountains like (L1)* object was at least 180 pixels in size then it was indeed a mountain object (Fenneman 1931). Therefore, two subclasses of the *mountains like (L1)* class were defined:

(a) *mountains (L1)* (tentatively-correct classified mountains) and

(b) *wrong classified mountains (L1).*

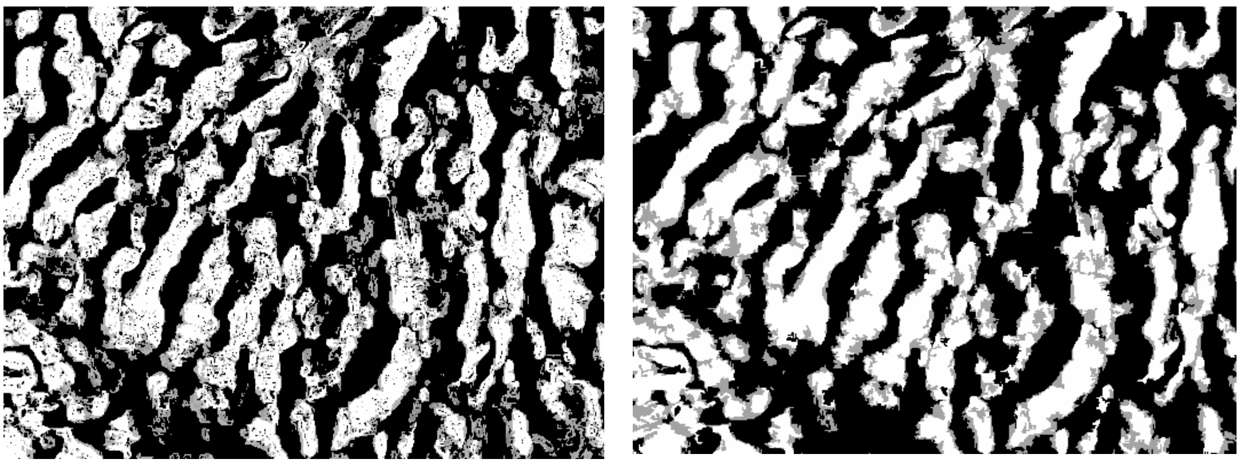
Given that *mountains like* objects have high slope gradient values, if a misclassified mountain object is near a *mountain (L1)* object, it is safe to assume that it is a piedmont slope object instead of a basin object.

Class *piedmont slopes like (L1)* was subdivided into two subclasses:

(a) *Wrong classified piedmonts (L1)* and

(b) *Piedmont slopes (L1)* (tentatively-correct classified piedmonts).

The feature used to distinguish the two subclasses was the distance of the objects of each subclass from the correctly classified mountains. If the distance was "just a few pixels", then it was assigned to the *piedmont slopes (L1)* subclass, otherwise to the *wrong classified piedmonts (L1)* subclass.



(a) (b)

Figure 4. Basins appear black, mountains appear white and piedmonts appear gray. (a) The first classification result of terrain objects. (b) The final classification result of terrain objects.

Finally, the class *basins like (L1)* was divided into two subclasses :

(a) *Basins (L1)* (tentatively-correct classified basins) and

(b) *wrong classified basins (L1).*

The feature used to distinguish these two subclasses was a constraint on the area of the segments: the area of the objects of the second subclass should be "relatively small". The proper fuzzy membership function was defined for the class *wrong classified basins*, while the subclass *basins* was defined as complementary to the other. A classification was made and object fusion was applied to group the objects of these classes in the structure hierarchy.

From the fusion of the classes of the second stage, three new categories were generated: *mountains (L2)*, *basins (L2)* and *piedmont slopes like (L2)*. By this fusing, the *wrong classified basins (L1)* and the *piedmont slopes (L1)* of the second phase were merged into the category *piedmont slopes like (L2)*, and thus the noise in the interior of the mountain objects was added to the new category *piedmont slopes like (L2)*. In order to get rid of this noise, remaining on the mountain objects, the class *piedmont slopes like (L2)* was further subdivided into:

(a) *piedmont slopes (L2)* and

(b) *wrong classified piedmont slopes (L2).*

The definition of the class *piedmont slopes (L2)*, took place with the criterion that piedmonts should have neighborhood relationships not only with the *mountains (L2)* objects, but also with the *basins (L2)* objects. A classification of the third stage knowledge base was implemented for the extraction of terrain objects. At this time, took place a fusion of the classes *wrong classified piedmonts (L2)* and *mountains (L2)*, which led to the final extraction of the terrain objects (*piedmont slopes (L3)*, *mountains (L3)* and *basins (L3)*), since the noise has been removed from all objects by refinement and regrouping to proper super-objects. The finally classified terrain objects appear in Figure 4b.

Segmentation of 1-degree DEM and Geomorphological Feature Extraction

After extracting the geomorphologic features from the GTOPO30 DEM, followed the extraction of alluvial fans step. For this purpose, the above procedure provided extra information to be used in classification steps as described bellow. For the alluvial fan extraction, the ASTER image and the 1 degree DEM and the slope image were used. The first step involved multiresolution segmentation. Three segmentation levels were developed in a top down approach starting from the coarser level and ending at the finer level.

At the first segmentation level, the objective was again the automatic extraction of the largest in size physiographic features (mountain ranges, basins and piedmonts), so that to use them at the later levels of classification for the extraction of finer geomorphological features (e.g. landforms). Segmentation of Level 1 was followed by classification of the primitives into semantic objects. A similar classification approach was followed as before. Since the present DEM resolution was 75m, while the GTOPO30 resolution was 1 km, certain parameters of the segmentation as well as of the limits of the membership functions for the slope image, had to be modified to take into account this resolution change. The change of the limits of the slope fuzzy membership functions was necessary due to the microrelief presence within the DEM of finer resolution, which caused more noise to appear.

The overall purpose for the extraction of physiographic features was their use in the classification of alluvial fans since they provided the contextual framework to create logical rules which would constrain the classification of alluvial fans in this higher physiographic level and thus optimize their border. The classification hierarchy appears in Figure 5, together with the results of the classification of the physiographic features.

Segmentation of Satellite Image Data

At the second level, the ASTER image data with the larger resolution of 15m (channels 1 to 3) were segmented with a scale parameter of 10 and almost exclusive spectral criteria since for this level a Nearest Neighbor classification was desired. The final selections for the color and shape criteria were 0.9 and 0.1 correspondingly. The shape criteria were set equal to 0.5. The results of the second level segmentation are shown in Figure 6.

At the third segmentation level, both the spectral and elevation data were used. Because of the different nature and resolution of these data, different weights were assigned to each. To the three channels of ASTER data, with a resolution of 15 m, the weight of 1 was assigned. The low resolution ASTER channels (4-14) were not used. The weight of 0.3 was assigned to the DEM and slope data sets. The aim for the segmentation of this level was to obtain primitive objects similar in size to the small alluvial fans and this was achieved with a scale parameter of 80. The color and shape parameters were set through trial and error procedure to 0.7 and 0.3 correspondingly, while the compactness and smoothness were set to 0.5 each. The result of the third level segmentation appears in Figure 6.

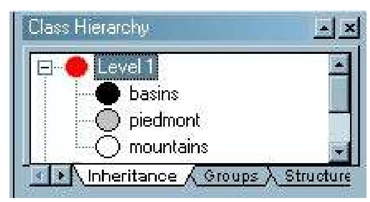


Figure 5. Left: The physiographic map produced from the automatic feature extraction technique as applied to the DEM of Figure 2. Right: The final class hierarchy of the knowledge base.

Extraction of Alluvial Fans

The second level classification had as basic objective the best possible spectral classification of third order landforms such as alluvial fans and subsequently the development of spatial and contextual rules (class related features) between the spectral classes towards the optimal final classification. Following the segmentation of the second level, which was based on the ASTER image, the following classes were initially defined: *Alluvial materials*, *Mountains*, *Basin floor salt deposits* and *Basin floor sediments*. Representative training samples were defined for each category within the spectral pattern space and the Nearest Neighbor operator was applied. Spectral classification was implemented without class related features which was to be further refined bellow.

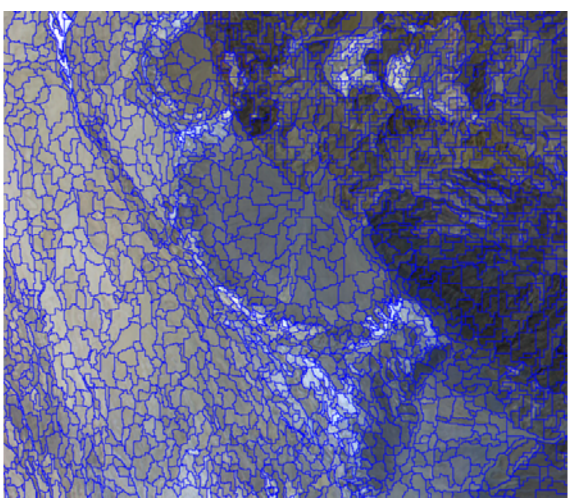
Furthermore, in order to get rid of misclassifications resulting from isolated objects of each group which were spectrally confused and thus classified into another class, a spatial neighborhood relationship rule was added to each of the categories *Alluvial materials* and *Basin floor sediments* and classification took place with class related features in five iterations so that to obtain classification stability.

Even after the last classification, there was one more heuristic which could be used towards better classification. As a rule, alluvial fans are deposits of the piedmont plain and the head of an alluvial fan is located right at the downstream end of the drainage network (where a stream pours abruptly into a basin at the startup of the creation of an alluvial fan) (Bull 1977, Hunt 1975, Rachocki 1981, Fenneman 1931, Pandey 1987). Generalizing this rule, it can be reasonably assumed the heuristic that all alluvial fans should be located on the piedmont plain, perhaps extending slightly downslope of the piedmont plains into the basin. As a reminder, in the first level, the piedmont plains have already been extracted, therefore this heuristic needs to check if all alluvial fans are almost complete super-objects of piedmont plain objects extracted in Level 1.

To implement this heuristic, first two new subclasses of the *Alluvial materials* class were identified: *Alluvial materials on piedmonts* and *Alluvial materials not on piedmonts*. For the definition of the first subclass, the feature "existence of piedmont subobject" was used to compute the existence of piedmont plain objects existing exactly bellow each processed object of the second level, and only those *Alluvial materials* objects were post classified as *Alluvial materials on piedmonts.*

The above described features and rules were applied after the projection of the piedmont plains from the first to the second level and resulted into the definition of the *Alluvial materials on piedmonts* subclass. What was left to be further defined was the subclass *Alluvial materials not on piedmonts*, which was further refined into two subclasses: *Alluvial materials near piedmonts* and *wrong classified alluvial materials*. *Wrong classified alluvial materials* were considered those located further away from the piedmonts, through a fuzzy membership function S type. With the implementation of classification with class related features, the final results were obtained as shown in Figure 7.

The objective of the third level classification was the final border definition of alluvial fans with emphasis on the larger fans. Towards this purpose the classes *alluvial fans* and *not alluvial fans* were defined as following. For the class of *alluvial fans*, two features "relative area of *Alluvial materials on piedmonts* subobjects" and "relative area of *Alluvial materials near piedmonts*" of the second level were used, in order to project two different classes of the second level , into a new class in level 3. Class *Not alluvial fans* was defined as opposite to the *Alluvial fans* class. Figure 7 shows the result of the final interpretation of alluvial fans.



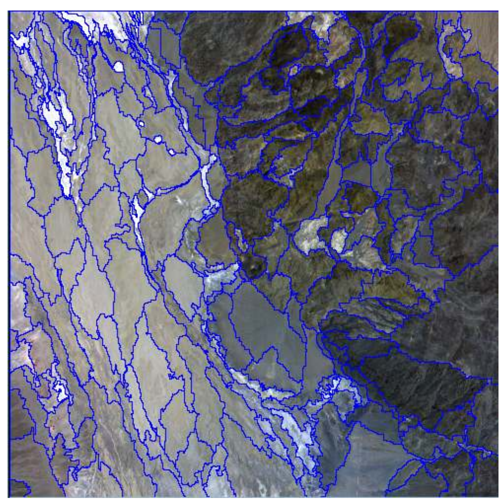


Figure 6. Left: The second level of the multiresolution segmentation applied to the ASTER dataset. Right: The third level of the multiresolution segmentation applied to the ASTER and 1 degree DEM dataset.

DISCUSSION OF RESULTS

The present approach shows satisfactory results both as it concerns the cartographic value of the final map but also as it concerns the new approach to the solution of the specific image interpretation problem provided through low (*multiresolution segmentation*) and high level (*knowledge-based fuzzy classification*) image analysis modeling in an object-oriented image analysis environment.

The extraction of terrain objects (Figure 4) was quite satisfactory in comparison to the physiographic map (Figure 8b) of Atwood. Measures of comparison can be the number and location of mountain ranges, their overall border outline, and the degree of generalization. As it concerns the number and location of the mountain ranges it appears that there is a great resemblance between the automatic extraction results and the physiographic map. The overall mountain border outline is almost the same except in certain cases where some discrepancies are present, but it is hard to advocate in support of the one or the other approach. At any rate the major mountain ranges are separable and distinct. The extracted mountain objects seem to be comparable to the results of the previous study of Miliaresis and Argialas (1999) (Figure 8c).

During the classification process of the mountain objects from the GTOPO30 DEM, there was severe presence of noise within the mountain objects as well as within the basins and the piedmont slopes. This problem was controlled by checking neighborhood relations between the objects that appeared as noise, and the tentatively-correctly classified objects. For example, some objects that were classified originally as piedmont slopes, and they were not located near a mountain object, they were classified in the category of basins since they could not theoretically stand alone. In order to eliminate the noise, the approach followed was an iterative method where at different stages the noise was eliminated by proper checks on neighborhood relationships, and repeated reclassifications and object fusions.

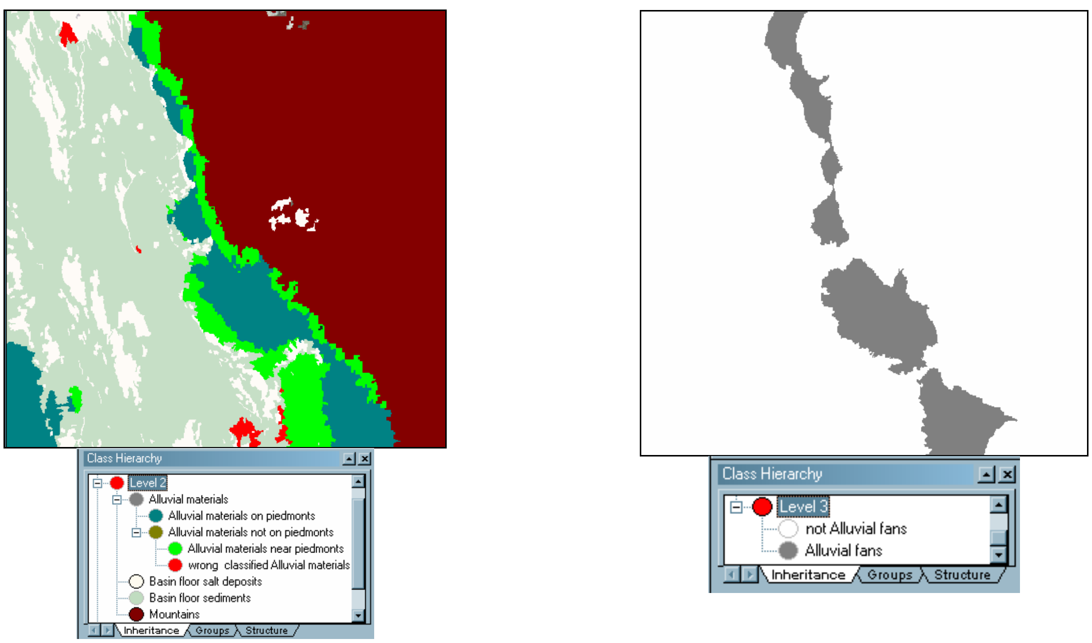
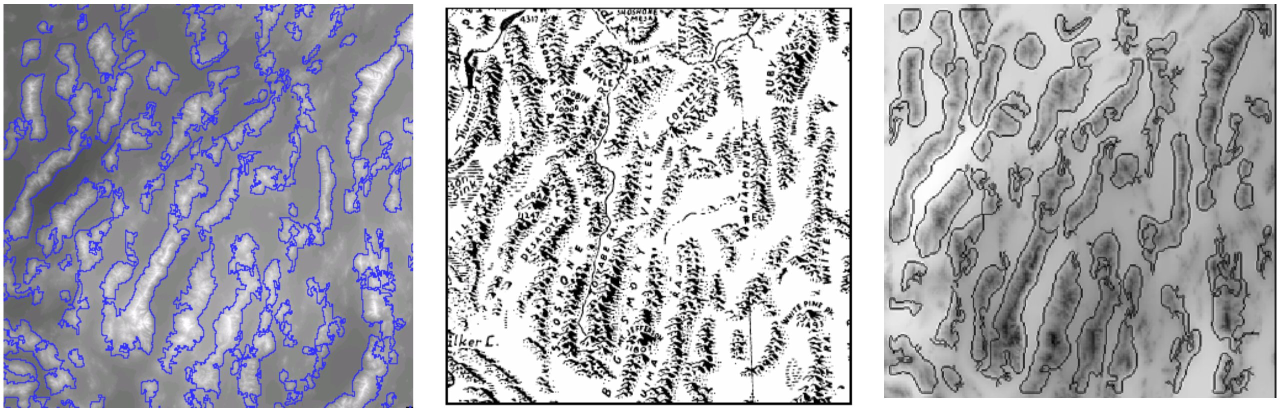


Figure 7. Left: The classification results of the second level and the class hierarchy used in the knowledge base. Right: The final classification of alluvial fans in level 4 and the class hierarchy used.



(a) (b) (c)

Figure 8. (a) The GTOPO30 DEM with the extracted mountain borders overlaid. (b) The physiographic map of Atwood. (c) The GTOPO30 DEM with the extracted mountain borders from Miliaresis and Argialas (1999).

This is the first time that a remote sensing software, *eCognition*, permits the use of so many image interpretation elements – spectral, shape, site, association, and context – within a uniform object oriented environment and offers the tools for modeling semantic relations towards an effective terrain object classification. It is also noteworthy that the present approach does not require seed points in contrast to the region growing algorithm used for terrain segmentation up to now (Miliaresis and Argialas 1999), since segmentation took place by region merging.

The alluvial fan extraction from ASTER images and the DEM, gave satisfactory results as it concerns the large size alluvial fans. Smaller size alluvial fans were delineated correctly, however, were not isolated, but appeared connected. Despite these problems, the delineation of alluvial fans with photointerpretation of the ASTER image could have had the same ambiguities as the alluvial fans are spatially coalesced.

Comparing the present object oriented classification with fuzzy logic to an older effort by the authors (Miliaresis and Argialas 2000), it appears compatibility of results (Figures 9). One of the advantages of the object oriented classification in *eCognition* for alluvial fans extraction is the simultaneous processing of digital data of various resolutions and types.

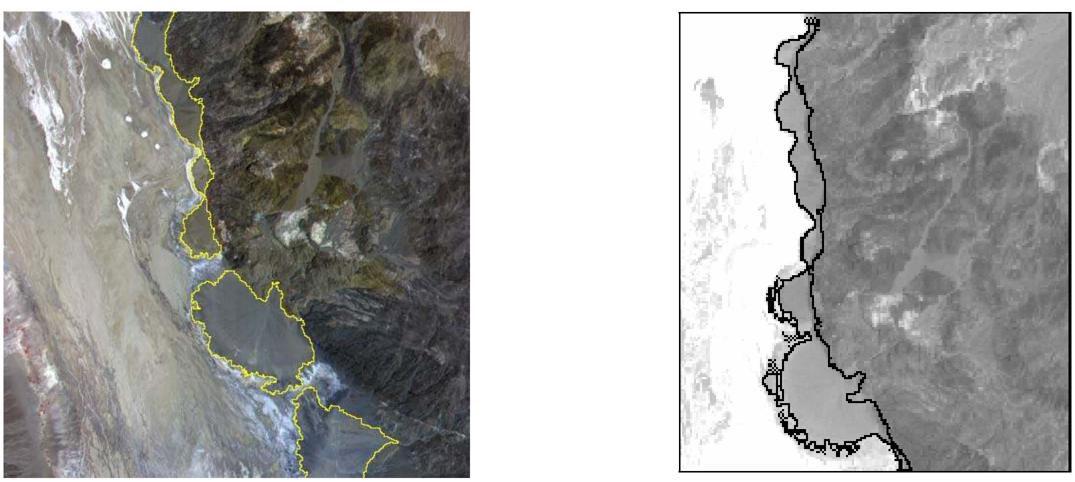


Figure 9. Left: The final borders of the alluvial fans of Level 3, displayed on top of the ASTER L1 RGB composite. Right: The results of a previous method for automatic extraction of alluvial fans from DEM and Landsat TM satellite data (Miliaresis and Argialas 2000).

CONCLUSIONS AND PROSPECT

In this paper an effort was made to test the low and high level object oriented image analysis techniques for the extraction of geomorphological features from the GTOPO30 DEM. In this effort, the results are satisfactory. It appears promising that such procedures could also be expanded in order to model not only terrain features at the physiographic level, but also on different landscape scales.

The object oriented image analysis approach for automatic extraction of alluvial fans, through *eCognition*, has set new prospects to the geomorphologic/physiographic feature extraction problem. New techniques and methodologies can be implemented, using knowledge based approaches, in order to provide more complex and effective results.

Concerning the functionality of the software, the methods provided for knowledge based classification (class hierarchies, fuzzy logic, spectral, geometric and spatial features) offer flexibility and assist in the creation of relatively complicated semantic descriptions, concerning the thematic classes of interest.

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