AUTOMATIC EXTRACTION OF ALUVIAL FANS FROM ASTER L1 SATELLITE DATA AND A DIGITAL ELEVATION MODEL USING OBJECT-ORIENTED IMAGE ANALYSIS

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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 alluvial fan terrain units. The study area was located in the Death Valley, Nevada, USA. The data used included an ASTER L1 satellite image and the 1° Digital Elevation Model. The methodology developed for alluvial fan extraction included preprocessing of the digital data: filtering of the Digital Elevation Model (DEM) for noise removal, a Fourier Transform Wedge filter for the elimination of striping in the ASTER data and geometric co-registration of the satellite and DEM data. A multiresolution segmentation technique was then developed, delivering object primitives at four resolution levels. At the first and finest level, three physiographic feature types (basins, piedmonts and mountains) were extracted from the DEM to be used in the rule-based fuzzy classification of the following levels. Then, a knowledge base including definitions of Alluvial materials, Mountains, Basin floor salt deposits and Basin floor sediments was implemented. The second level was classified by the nearest neighbour classifier using spectral information for the first iteration of the classification procedure. For a second iteration, the knowledge base was further expanded primarily with heuristics concerning contextual information of the alluvial materials related to the geomorphological features extracted at the first level. Finally, in the last level, a projection was made, classifying the image into two classes: Alluvial Fans and Not Alluvial fans. The method gave good results in detecting alluvial fan units, working best for large shape alluvial fans. Some minor problems were encountered for the smaller alluvial fans, due to the difficulty of their boundary representation. The results were compared to an alternative method for the extraction of alluvial fans and they were found satisfactory.

1. INTRODUCTION

This research concerns the automatic extraction of alluvial fans from 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 extraction is of significance to the remote sensing, geologic and civil engineering community.

The main objective of this research was the investigation and implementation of object oriented image analysis algorithms and fuzzy logic techniques within the *eCognition* environment for the recognition and classification of alluvial fans based on their spectral, topographic, topologic, geometric and contextual knowledge from digital elevation models (USGS 1-degree DEM) and multispectral ASTER L1 Satellite Data. The selected study area is in the Death Valley, USA, since the authors have done similar work in this region for many years (Argialas and Miliaresis 1996, 1997b). The results were compared to those of a previous work by the authors employing a different approach (Miliaresis and Argialas, 2000).

2. DATA USED - PHOTOINTERPRETATION

Data used included the 1-degree Digital Elevation Model with 75m grid size (Figure 1), available through USGS (http://edcwww.cr.usgs.gov/) and an ASTER Level 1 satellite image (Figure 2) 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.

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.

3. METHODOLOGY

3.1 Data Preprocessing

Before the actual object oriented image analysis, it was necessary to apply certain preprocessing so that to have the same reference system for all data and to handle certain acquisition errors.

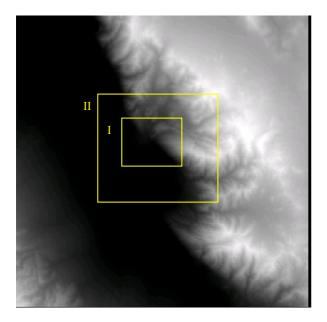


Figure 1. The 1-degree DEM provided by USGS for Death Valley (I and II are referenced in the following figures)

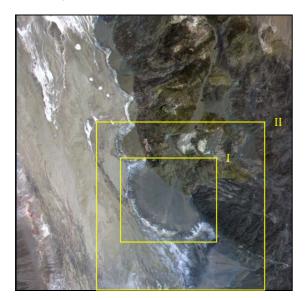


Figure 2. The ASTER L1 Dataset of Death Valley in RGB (321) composite (I and II are referenced in the following figures)

Within the DEM, noise was apparent in the form of linear features especially within the slope image (Figure 3). Thus, low pass filtering was applied for noise elimination employing finally a 3x3 smoothing filter since it was found that both 3x3 and 5x5 filters gave compatible results, while the 3x3 filter had the advantage of minimum loss of information (Figure 3). Followed the slope computation, employing the Gradient operator in ERDAS Imagine and the geometric registration of the DEM to the ASTER image. Since it was difficult to locate ground control points on the DEM, first a shaded relief map was created and it was used to locate eight ground control points with the aid of the topographic relief and the drainage network. A second degree polynomial was used. The final accuracy of the DEM registration was 1.5 pixels.

Furthermore, the ASTER image presented periodic line noise (striping) perpendicular to the satellite flight path. Given the periodic nature of this noise and that the periodic striping appeared on the Fourier Spectrum perpendicular to the noise lines of the image, Fourier filtering was judged appropriate to be applied.

To eliminate this periodic striping, appearing as a line on the Fourier spectrum, a low pass filter in the form of a wedge mask was applied using a Hanning Window function of 3° . Finally, the inverse Fourier transform was applied.

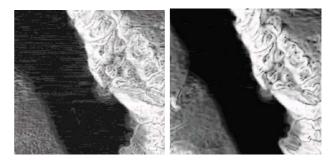


Figure 3. Left: The original DEM slope dataset with linear noise present in the basin region. Right: The DEM slope dataset after the 3x3 smoothing filter

3.2 Segmentation

Following the preprocessing, the ASTER image, the DEM and the slope image were imported in *eCognition*. The first step involved multiresolution segmentation. Four segmentation levels were developed in a top down approach starting from the coarser level and ending at the finer level. However, the presentation will follow a bottom up approach starting with the first level, so that to correspond to the classification bottom up process as presented in the section 3.3 bellow.

At the first segmentation level the objective was 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). Thus at the first level, the DEM alone was segmented into very small primitive objects with scale parameter k=10. A small shape criterion (0.3) was used since the size of the desired primitive objects was such that the compactness and smoothness criteria were not as important as in the case of larger primitive objects. The compactness and smoothness criteria were equal to 0.5 each. Figure 4 shows the segmentation of the first level where it is observed that in the upper right of the DEM, where the relief variation is greater, the resulted primitive objects, have had size almost equal to the DEM grid raster, as it was expected. The size of the primitive objects in the rest of the image is much larger due to the lower and smoother topographic relief.

At the second level, the ASTER image data with the larger resolution (channels 1 to 3) were segmented with a scale parameter of k=10 and almost exclusive spectral criteria since for this level a Nearest Neighbor classification was desirable. The final selection for the color and shape criteria were 0.9 and 0.1 correspondingly. The shape criteria (compactness and smoothness) were set equal to 0.5. The results of the second level segmentation are shown in Figure 5.

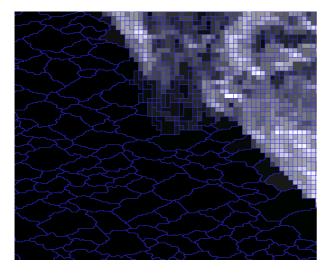


Figure 4. The first level of the multiresolution segmentation applied to the slope dataset. The region shown corresponds to the rectangle area I of Figure 1.

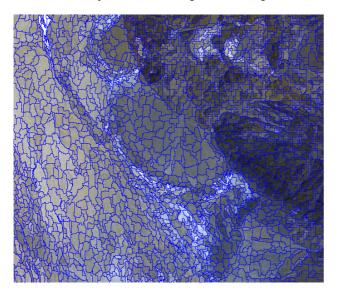


Figure 5. The second level of the multiresolution segmentation applied to the ASTER dataset. The region shown corresponds to the rectangle area II of Figure 2.

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. To the DEM and slope data sets the weight of 0.3 was assigned. 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 k=80. The color and shape parameters were set after trials 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 appear in Figure 6.

For the fourth level segmentation, the same two datasets were used with the same weights, however a scale parameter of k=250 was used so that the resulting primitive object sizes to resemble the larger sized alluvial fans. By a trial and error effort, the color and shape parameters were set to 0.6 and 0.4, while the compactness and smoothness criteria were set to 0.5

each. The results of the fourth level segmentation are shown in Figure 7.

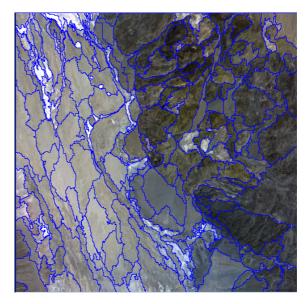


Figure 6. The third level of the multiresolution segmentation applied to the ASTER and DEM dataset.

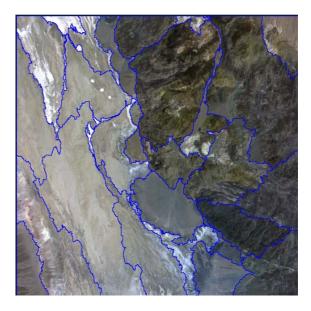


Figure 7. The fourth level of the multiresolution segmentation applied to the ASTER and DEM dataset.

3.3 Classification

Multiresolution segmentation was followed by classification of the primitive objects of each level into semantic objects. The object oriented classification included several stages. In the first stage, the thematic classes were identified and their classification features were defined. Classes and features were then represented within the object oriented knowledge base environment of *eCognition*. Classification followed with either sample selection or membership function definition.

3.3.1 Level 1

As it was suggested in the segmentation stage of level 1, the basic objective of this level was the automatic extraction of small geographic scale, and thus larger in size, physiographic features: mountain ranges, piedmont slopes and basins. In an earlier publication, Argialas and Tzotsos (2003) have developed the segmentation and classification of physiographic features from the GTOPO30 DEM with 1 km grid size. In the present work, a similar classification approach was followed, except as indicated bellow, since the present DEM resolution was 75m, while the GTOPO30 resolution was 1 km. Therefore, 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 membership functions was necessary due to the microrelief presence within the DEM of finer resolution, which caused more noise to appear. These changes had small range (1 to 2 degrees).

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 8, together with the results of the classification of the physiographic features.

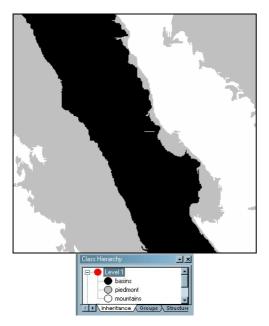


Figure 8. Top: The physiographic map produced from an automatic feature extraction technique (Argialas and Tzotsos 2003). Bottom: The class hierarchy of the knowledge base.

3.3.2 Level 2

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 so that to compute the distance in the pattern space, of each primitive object to each class sample. As a result, each object was assigned through fuzzy logic a membership value to each class. In the classification process besides the ASTER data, the DEM, and the slope gradient were also employed so that to take advantage of the topographic distribution of each landform (e.g. *mountain* objects are located in high elevation and steep slope areas). 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 been extracted, while in this second level, the alluvial fans are being extracted. Therefore, this heuristic needs to check if all alluvial fans are almost complete superobjects of piedmont plains extracted in Level 1.

The direct way to apply the stated heuristic, is to employ a feature to express the distance of an object at a super-object level to a class in a finer level (e.g., "relations to subobjects/distance to" similar to "relations to neighbor objects/ distance to"). Such a feature was not available in *eCognition* 3.0, therefore it was necessary to apply this heuristic through an indirect way: first to project the piedmont plains from the first to the second level and then to use the feature "distance to" which was available for the second level.

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 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. Wrong classified alluvial materials*. Wrong the piedmonts, through a membership function S type. With the implementation of classification with class related features, the final results were obtained as shown in Figure 9.

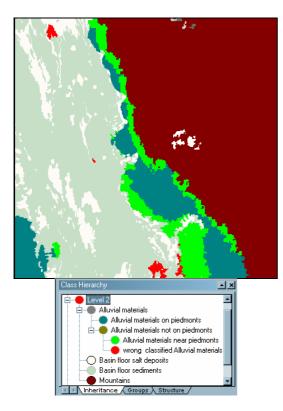


Figure 9. Top: The classification results of the second level, Bottom: the class hierarchy used in the knowledge base

3.3.3 Level 3

In the previous, second classification level, the alluvial materials from which the alluvial fans are formed were mainly classified. The purpose of the third level classification was the definition of the geometry mainly of the small sized alluvial fans. Additional aim was the border optimization of all classified objects, due to the greater level of abstraction and generalization of the third level. Therefore the classification of the third level took place exclusively through topologic and neighborhood class related features. A projection of the second level classes was employed, using features such as "relation to subclasses/ existence of" and "relation to subclasses/ relative area of". The "relative area of" feature expresses the area covered by sub-objects assigned to a defined class divided by the total area of the image object concerned on a higher level (eCognition User Guide 2003). Through such features, the definition of the same classes, as those of the second level took place, and the projection was performed through a classification with class related features. The results of the third level classification are shown in Figure 10.

3.3.4 Level 4

The objective of the fourth 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* subobjects" of the third level and "relative area of *Alluvial materials near piedmonts*" of the second level were used, in order to project two different classes of levels 2 and 3, into a new class in level 4. Class *Not alluvial fans* was defined as opposite to the *Alluvial fans* class. Figure 11 shows the result of the final interpretation of alluvial fans.

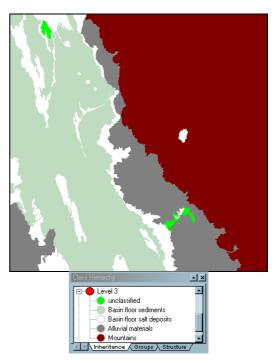


Figure 10. Top: The classification results of the third level. Bottom: the class hierarchy used in the knowledge base

4. DISCUSSION OF RESULTS

The present object oriented classification with fuzzy logic, in comparison to previous work by the authors, showed satisfactory results concerning both the final map products and the new approach within the eCognition environment. 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, weren't isolated, but appeared connected. Perhaps further morphological postprocessing of the present results could lead to the separate delineation even of those difficult, small-sized fans. 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 12 and 13). One of the advantages of the object oriented classification in eCognition for alluvial fans extraction, is the simultaneous

eCognition for alluvial fans extraction, is the simultaneous processing of digital data of various resolutions and types. Some elements needed for *eCognition* is a programming environment for new feature definition by the user and some basic pixel based processing (e.g. pixel based classifiers) which is often needed for certain phases of image analysis.

5. CONCLUSIONS AND PROSPECT

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.

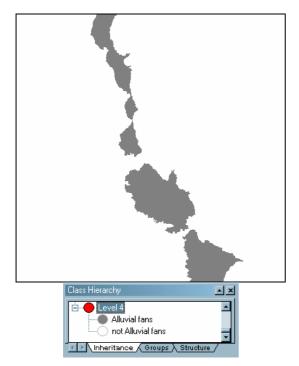


Figure 11. Top: The final classification of alluvial fans in level 4. Bottom: The class hierarchy used.

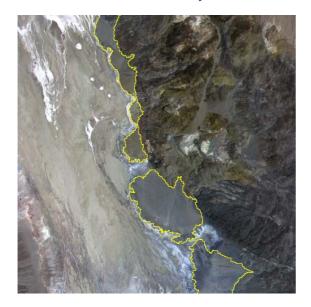


Figure 12. The final borders of the alluvial fans of Level 4, displayed on top of the ASTER L1 RGB composite.

The environment of *eCognition* provides many features (fuzzy logic, class hierarchy, knowledge base, class related features, multiresolution segmentation) to be used in various Remote Sensing applications.

As a prospect for geomorphological feature extraction, new knowledge-based object-oriented methods could be applied in the future for physiographic feature extraction at different geographic scales.

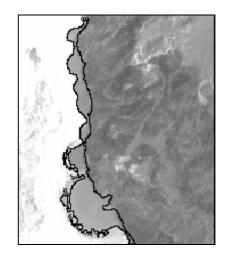


Figure 13. The results of a previous method for automatic extraction of alluvial fans from DEM and Landsat TM satellite data (Miliaresis and Argialas 2000).

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