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A Machine Learning approach to aerial photointerpretation and mapping

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***Abstract* – In the project "ARCHEO 3.0" a Machine Learning (ML) system for automatic contouring of the stratigraphic units of an archaeological excavation has been experimented. In this research, we have applied the same ML algorithm to aerial color photographs that represent very important tools in the study of ancient topography and landscape archaeology. Aerials of the Vulci necropolis, one of the most important cities of ancient Etruria, have been used. These photos, both vertical and oblique, have been chosen because the marks had been studied and analyzed in a recent PhD work in Ancient Topography. In particular, the traditional mapping method has been compared with the results obtained by means of automated ML algorithm. This experiment has demonstrated that the developed ML algorithm can be applied to aerial photographs for the recognition of archaeological traces, with interesting development prospects.**

Keyword: Machine Learning, aerial photography, archaeological mapping, landscape archaeology, ancient topography, crop-marks, Vulci.

I. INTRODUCTION

In the framework of the project Archeo 3.0, funded by the Regione Toscana and developed by Consiglio Nazionale delle Ricerche, a Machine Learning (ML) algorithm for the automatic drawing of contours of stratigraphic units has been tested in archaeological excavation [1, 2]. Here we decided to extend the ML analysis to aerial color photographs that represent a very important tool in the study of ancient topography and landscape archaeology.

It is well known that buried archaeological structures produce visible marks on aerial photographs that, correctly interpreted, allow defining their shape and perimeter (contour).

There are different types of tracks: damp-marks, crop-marks, soil-sites, shadow-sites [3-5]. Crop marks are essential for our research because they are characterized by high color contrast. In fact, archaeological structures, interacting with the rooting apparatus of the vegetation, can deeply influence its growth that can thus be reduced or enhanced. This difference can be easily recognized in aerial photographs considering the chromatic contrast. For example, in correspondence to the graves dug in the ground or defensive ditches, the vegetation will be taller and thicker, resulting in a dark green color; on the contrary, in correspondence with masonry structures or roads, plants will be lower and thinner resulting in light green or yellow (fig. 1).

In the traditional archaeological method, marks that are recognized in the photos are digitally drawn on a topographic map (CAD), a process that takes many days to generate the final results.

The aim of this project is the development of an automatic or semiautomatic system that allows speeding up the time of graphic restitution, drawing the outlines of the archaeological mark or helping the archaeologist in the interpretation with the delimitation of the areas affected by underground structures. These outlines, shown on the topographic map, will be crucial in protecting archaeological heritage.

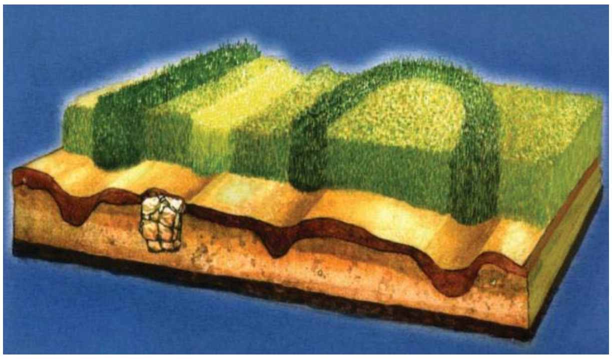

Fig. 1. The effect of buried archaeological features on the growth of crops.

II. MATERIALS AND METHODS

A. Aerial photography

In this research, aerial photos of the Vulci necropolis have been used. Vulci was one of the most important cities of ancient Etruria from which, according to Latin writers, Servius Tullius, the sixth king of Rome, came from.

Both vertical and oblique photos of Vulci have been considered in a recent PhD work in Ancient Topography, in which the marks were studied and analyzed by means of a traditional mapping [6, 7]. These images were ideal candidates for testing the reliability and accuracy of the automatic (or semi-automatic) method based on ML algorithm. For this aim, a comparison with the automated results and the archaeological map, has been conducted (fig. 2).

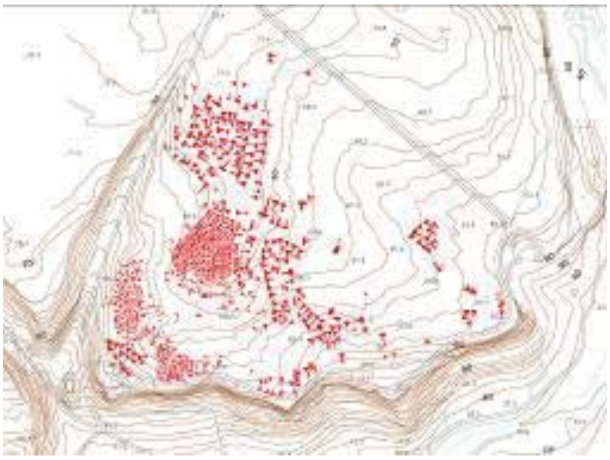

Fig. 2. Vulci. Poggio Mengarelli. Traditional method mapping of tombs (by G.F. Pocobelli).

Fig. 3. Vulci. Planimetric photography. Details of crop-marks of the shaft tombs.

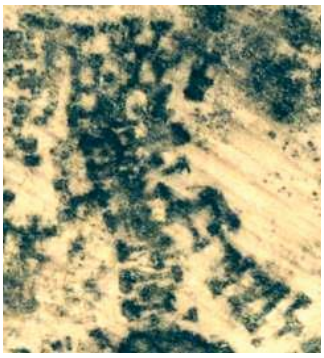

Fig. 4. Vulci. Planimetric photography. Details of crop-marks of the chamber tombs.

Fig. 5. Vulci. Oblique photography. Details of crop-marks of the chamber tombs.

In particular, it has been considered a 1996 vertical photo of a sector of Poggio Mengarelli (N of the ancient city) - used as a necropolis from the 8th to the 4th /3rd c. BC. It shows clearly many rectangular crop-marks, produced by underground shaft tombs (fig. 3), and "T" crop-marks of chamber tombs (fig. 4). The tombs were excavated in a very tender tufa bank, in which it was easy to make simple shaft tombs but also architecturally more complex graves, with a long ramp (dromos) descending to the rectangular atrium (i.e. the T recognizable by the traces) leading to the hypogeum chambers where aristocratic families were buried from the 7th c. BC onwards.

Some oblique photographs of the same necropolis sector have been also considered in this work. They were made at low altitude in 2001, in which the same traces were visible but with a different angle (fig. 5).

B. Machine Learning

A variety of problems are now currently solved with Machine Learning techniques. It ranges from detecting spam, to product recommendation as well as medical diagnosis and financial analysis. It not surprising that also in the archaeological domain, ML finds room for a plethora of applications [1, 2]. In this contest, one of the main aims of ML, is to group the unlabeled elements in a dataset depending on specific features (clusters): this task is commonly referred to as unsupervised learning. This approach is particularly interesting, since in archaeology, the features to be identified are generally partial or completely unknown.

Moreover, this approach results to be extremely promising because it requires minimal human intervention. This appears even more appealing in all the cases in which archaeology deals with images. In fact, a preliminary division (clustering) of the digital image can be performed by means of ML without providing the algorithm with any information on the image under test.

This can help the archaeologist in the identification of features that are not easily observable with the naked eye.

Among the numerous unsupervised ML algorithms for clustering, we have considered *k*-means clustering, due to its ease of use and robustness. This algorithm is able to partition the dataset (in this case the image) into a number of clusters established a priori by the operator.

The algorithm we have developed is based on three steps: in the first one, the operators set the number of clusters (*k*). In the next step, the color coordinates (e.g. RGB, HSL..), for each pixel of the image under test, are extracted, and *k* barycenters are defined in a random fashion. A barycenter is defined as a real location representing the center of a cluster. Every pixel is allocated to a cluster through reducing the in-cluster distance between all pixels. In other words, the pixel is assigned to its closest cluster center according to a distance function. For this aim, in the third step, a distance measure, based on Euclidean distance between the color coordinates of each pixel and the actual barycenters, is used for updating the clusters areas and hence the barycenter positions. The procedure is repeated until no further change occurs in the barycenter positions.

The outputs of the algorithm are *k* images in which all the non-zero pixels belong to a specific cluster. The *k* images are then combined, by assigning an 8-bit number to each pixel in a cluster, into a composite image (in false colors). This image is finally used with standard edge detection technique (such as Sobel or Canny filtering) to highlight the contours - in this case - of the tombs. It should be remarked that the results are subjective by the number of clusters set a priori. In this work, for the sake of homogeneity, all the images have been processed considering the same color coordinates and number of clusters (RGB, *k*=3).

III. RESULTS

In this research we have chosen to use only color photographs, deliberately excluding B/W photographs since the ML developed system works very well with color clusters. Moreover, historical B/W aerial photos are currently used in advanced experimentation conducted by Italian National Photographic Aerial Archive (AFN-ICCD) in Rome with Bruno Kessler Foundation (FBK) in Trento [8, 9].

Several areas from Poggio Mengarelli site (Vulci) have been considered for color clustering. The false color images obtained with RGB color coordinates and 3 clusters, for four areas have been presented in fig. 6. The aerial original image with overlaid the contours obtained at the end of the edge detection step, have been presented in figg. 7-10.

It results that the algorithm can recognize with a good degree of approximation the contours of the single tombs.

An in-depth analysis shows that the elaborations on aerial planimetric photographs are very detailed and with precise contours on many of the visible traces. In some zones instead, in particular where the vegetation color is rather uniform, the system fails to distinguish the single tombs and the contour includes large sepulchral areas. In other cases, instead, where the human eye recognizes the regular forms of the graves, the computer is not able to detect marks.

We obtained a better result on the oblique photographs. The algorithm correctly distinguishes and highlights the profiles of the individual chamber tombs, with little loss of information.

The difference in terms of results could depend on the different degree of detail of the images. The coverage rate of vegetation affected the ability to read the tracks. The time of photo coverage is also important: in addition to different years, the oblique photos were taken at the end of June, with vegetation in the initial state of growth, while the planimetric photos in the second half of July.

On the other hand, we are not able to assess how much the difference in angle of coverage has favored the recognition of forms, perhaps helped by shadows and microrelief.

About mapping, we find a substantial correspondence with what is indicated with the traditional method, with a greater realism of the outline obtained with ML. The slight differences are due to the need to geometrically correct the oblique image, which is not necessary for planimetric photographs. The intervention of man, however, is still necessary to integrate what is not detected by the algorithm.

As far as the processing time, the results are excellent. With a standard laptop of the last generation, only few tens of seconds were needed to process with ML each photograph shown in this work.

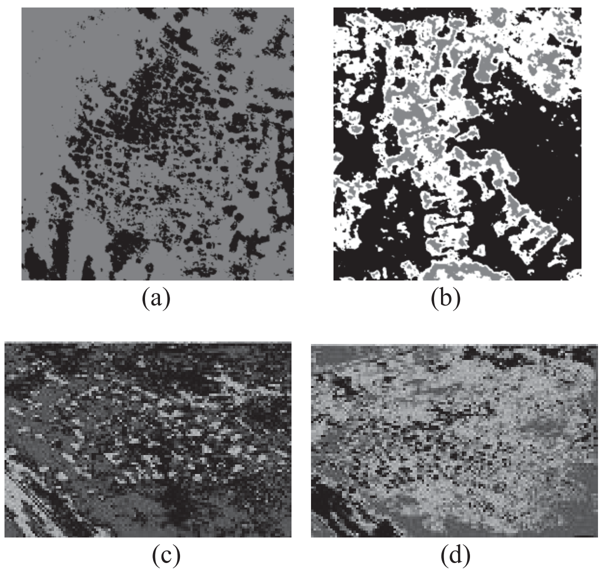

Fig. 6. Vulci. Poggio Mengarelli. a), b), c), d) False color images after color clustering with k=3 and RGB color coordinates.

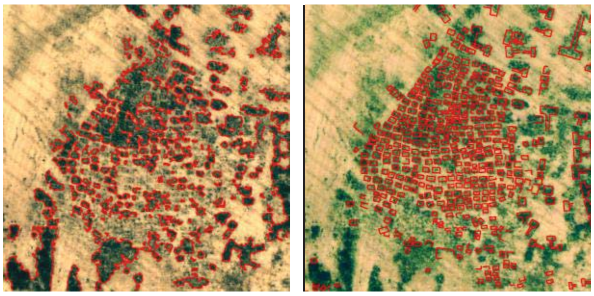

Fig. 7. Vulci. Poggio Mengarelli. Left) aerial original image with obtained contours overlaid; right) aerial original image with traditional method mapping of tombs.

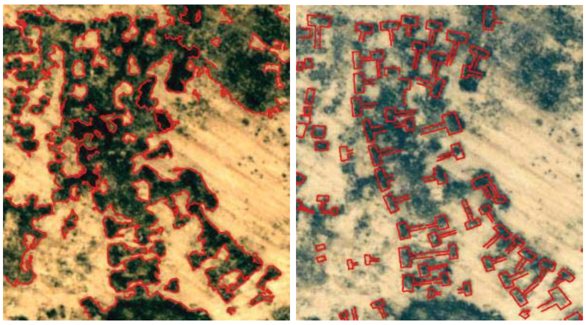

Fig. 8. Vulci. Poggio Mengarelli. Left) aerial original image with obtained contours overlaid; right) aerial original image with traditional method mapping.

Fig. 9. Vulci. Poggio Mengarelli. Left) aerial original image with obtained contours overlaid; right) map with the traditional method of mapping of the marks.

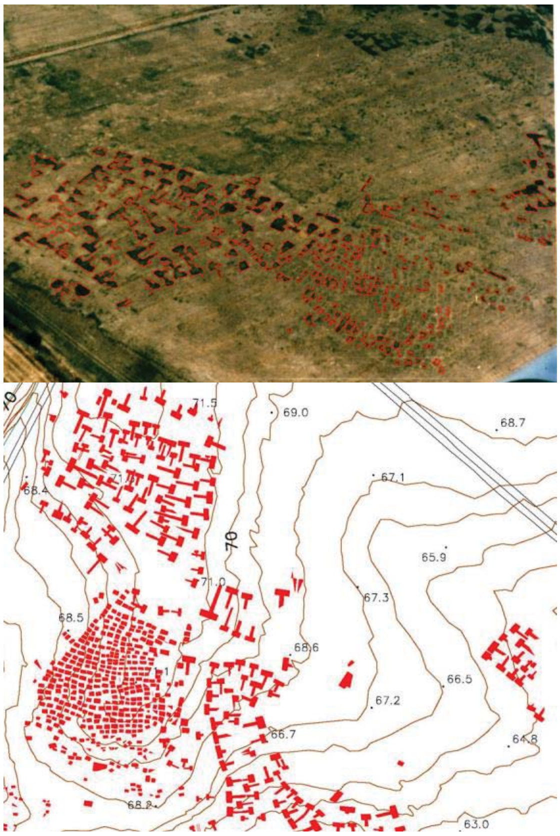

Fig. 10. Vulci. Poggio Mengarelli. Left) aerial original image with obtained contours overlaid; right) map with the traditional method of mapping of the marks.

IV. CONCLUSIONS

These preliminary experiments have demonstrated that ML developed in the framework of the ARCHEO 3.0 project for the identification of archaeological strata under excavation, with appropriate calibrations and corrections can also be applied to aerial photographs for the recognition of archaeological traces, with interesting development prospects.

Comparison with the traditional mapping method suggests that the ML system needs further improvements. Fig. 7 shows the mapping of 423 tombs with the traditional method, while the algorithm recognizes with a good degree of approximation the outline of 70 tombs (16.5%). The result obtained with fig. 8 is better: the algorithm defines 23 tombs while the human eye recognizes 71 shapes (32.4%). However, the limits of the areas where the vegetation is higher are defined very well. In these areas, the human eye can distinguish numerous tombs that the algorithm cannot define. However, it is also very important for the archaeologist to circumscribe the perimeter with the archaeological marks. As mentioned above, the best results have been obtained with the oblique photographs (figg. 9-10). The ML system recognizes 226 shapes while the traditional mapping detects 527 tombs (42.9%). The main reason for this result can be found in the different degree of growth of vegetation among the images used: lower in oblique photos, more luxuriant in the verticals. Instead, we cannot evaluate how much the angle of recovery has influenced the ability to recognize shapes through the microrelief shadows.

Failure to identify the traces recognizable by the human eye - one of the limits shown by the system - can be overcome by having the same image processed several times with different parameters, to create different levels of reading that, superimposed, can integrate any unwanted gaps.

Image definition is another element to be improved to achieve better results. The original photographs used in this experiment are paper prints obtained with non-professional scanners at an average resolution (300 dpi). Increasing resolution with a suitable scanner could lead the ML algorithm to perform better. Other tests may be done: f.i. using images treated and corrected images with filters for the improvement of tone, contrast and colors, so as to increase the possibility of ML reading.

For the overall evaluation of the results obtained, the time taken to map the tracks is crucial. With the traditional method and the expensive technical equipment for cartographic restitution, certainly more precise and complete, it takes two days of work, while the ML system and a standard computer require only a few tens of seconds.

However, these initial tests can demonstrate it is foreseeable that ML algorithm, with the necessary calibrations, can greatly speed up the time of graphic restitution, helping the archaeologist to map, with an error of decimetric approximation, buried archaeological remains and to plan any excavation and protection of the archaeological heritage.

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