ARCHAEOLOGICAL SITES STUDIES BASED ON NEURAL COMPUTATION TECHNIQUES

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ABSTRACT/RESUME

Some previous archaeological studies developed by the investigation group are based in the application of Artificial Neural Networks to detect special items in aerial or remote sensing[1] scenes[2], [3]. As Artificial Neural Networks have been widely used to solve problems related with pattern recognition and classification, a good performance is expected in the detection of certain image zones susceptible to contain archaeological remains, such as buildings, ruins, roads or ways. In this paper we present the study carried in on the area of Cáparra archaeological site.

1. INTRODUCTION

One of the application fields of remote sensing is the archaeological studies; it must be exploited to deduce the maximum history information [4], [5]. Unsupervised pattern recognition methods such as Principal Component Analysis (PCA) or Hierarchical Cluster Analysis (HCA) [6], [7], and supervised methods such as Discriminant Analysis have usually been applied to study multivariate archaeological data [8].
On the other hand, ground penetrating radar (GPR) provides a powerful and high-resolution tool for subsurface remote sensing. It offers a rapid and inexpensive method for the investigation of the shallow sub-surface and has been widely used as non-destructive technique in a variety of disciplines, such as engineering, geotechnical, archaeology, forensics, and many others [9]. This technique can be used to validate the results given by the neural network model, which in addition is also applied to the treatment and study of the ground penetrating radar images.
Cáparra's archaeological site is formed by the remains of a Roman town that could have been founded during the era of Emperor Augustus, close to the then newly created iter ab Emerita Asturicam, a road known in present times as Vía de la Plata which connects the North western and South western regions of Spain. The aim of our studies is to evaluate the performance of Self-Organizing Neural Network in image classification tasks related with Cáparra ruins. Given an image, the network is trained to distinguish between a certain number of different materials, which are chosen depending on the training parameters. This method is especially sensitive to certain aspects, like ground elevation or borders. The performance of this method can be verified applying ground penetrating radar techniques. In our previous studies, after using the Self-Organizing Map on airborne photographs, it was able to detect roads and ruins in Cáparra archaeological site (in example, the ancient road Ruta de la Plata, or the Roman theatre). This fact has contributed to a better knowledge of one of the many small towns in the region known in Roman times as Lusitania, including its urban structure, thereby satisfying society's cultural interest in this type of archaeological site.

The rest of this document is organized as follows: the section 2 is dedicated to describe Cáparra archaeological site. The section 3 is used to introduce the Ground Penetrating Radar, with which part of the neural network results were tested. In section 4 we present the general structure of the used SOM, its training and its processing. The section 5 shows the previous results of our experiments, and the section 6 introduces some possible improvements in archaeological sites investigation, concerning the use of CHRIS images, while section 7 is the summary and conclusions of our studies and future research.

2. ARCHAEOLOGICAL SITE AND IMAGES

The road known as the Vía de la Plata corresponds to road 24 of Antonino's itinerary, the iter ab Emerita Asturicam (from Mérida to As-torga). That it connects two distant points in the west of the Iberian Peninsula sets it out as a major communications axis, since it breaks the usual radial disposition of the Peninsular communications. The Roman town of Cáparra was 110 Roman miles (milia passuum, equivalent to 1480 m) from the starting point of the road in Mérida (Augusta Emerita). In traversing the town the road forms the decumanus maximus (longitudinal axis), to which the

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two lateral gateways were added in front of the domestic areas. The road is 4.5 m wide in the urban zone, with an extra 2.8 m added at each side of the two lateral gateways. The tetrapylon (four-gated arch) was placed in the geometrical centre of the decumanus, at the junction with the kardo (transverse axis). This arch has an 8.41 x 8.41 m2 ground plan, and the road under the arch narrows to 3.44 m in width. The town is approximately 15 ha in area. Parts of the forum (3760 m2), the thermal baths (3760 m2), and the domestic area (1070 m2) have already been excavated.

The first references to the ruins of Cáparra were given by the Italian Mariangelo Accursio in 1525 [10], although archaeological work itself did not start until the 20th century. The first interventions in 1929 were aimed at attempting to define the function of some of the buildings, and the last in 2001 corresponded to a major excavation campaign carried out in the framework of the Alba Plata project, with the purpose of adapting the site to make it suitable for visits [11], [12], [13], [14].

For this work, we had available the photographic collection covering 1956 till the present in the Archaeology Laboratory of the Universidad de Extremadura. To optimise their analysis, we digitalized the images using a photogrammetric scanner model Vexcel UltraScan 5000, with a maximum precision of ±2 µm and a maximum optical resolution of 5080 dpi. Of the many photographs that were analysed, we shall here discuss three in particular, that were split into five for a better analysis. Their details are as follows: photograph 1956: 23 x 23 cm2 black and white aerial photograph, taken from an aeroplane in 1956, 1:36000 scale, pixel size 20 µm, corresponding to Figure 1 (b) and Figure 1 (d); photograph 1987a: 23 x 23 cm2 black and white aerial photograph, taken from an aeroplane in April 1987, 1:5000 scale, pixel size 20 µm, corresponding to Figure 1 (a) and Figure 1 (c); photograph 1987b: orthoimage from the Instituto Geográfico Nacional, obtained by the Landsat 5 satellite, T.M. sensor, in September 1987, 1:100000 scale, pixel size 85 µm, corresponding to Figure 1 (e). Figure 1 represents all the previously explained images.

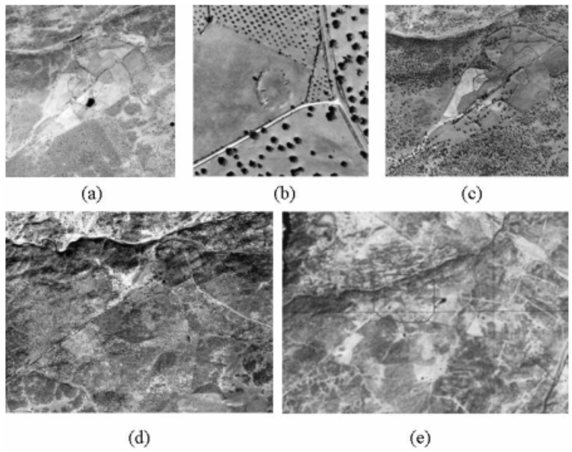

Figure 1. From top left to right, and from top to down: (a) 0004detalle.jpg, (b) 188detalle.jpg, (c) 598Adetalle.jpg, (d) cap562.jpg, (e) ortoimagen.jpg.

3. GROUND PENETRATING RADAR (GPR)

GPR consists principally of a laptop, a control unit, a transmiter and a receiver. The transmitter generates a very short (1-20 ns) high voltage monopulse and transmits it into the antenna, which emits electromagnetic radiation of a specific frequency (in the frequency band 10 MHz - 2.5 GHz) into the soil. By moving the antennas over the ground, the receiver records electromagnetic waves reflected from boundaries of sub-surface material having different dielectric constants and an image of the shallow subsurface under the displacement line is obtained.

The ground penetrating radar prospecting was done using a RAMAC/Mala GPR system equipment with a screened antenna of 500 MHz of central frequency [15].

Once delimited the prospecting place, the experimental procedure was centered upon four points: 1) delimitation of the propagation speed of the electromagnetic waves into the soil; 2) optimization of the system parameters; 3) making of the profiles and of the subsoil images and 4) filtering of the ground penetrating images, to accent the most important anomalies.

4. SOM NEURAL NETWORK

During the last decade, artificial neural networks have been success-fully applied to the analysis and interpretation of aerial imagery [16], [17], [18]. The advent of ANN approaches in image analysis is mainly due to their power in pattern recognition and classification. One of the most commonly used ANN model in classification of image data is the known as the Back-Propagation [19] but requires a number of test samples with known answers.

Artificial Neural Networks are useful methods for archaeological studies capable of overcoming critical points of statistical techniques such as the influence of noise and outliers. The network known as Self-Organizing Map (SOM) or Kohonen Maps [20] can be considered an interesting alternative for the processing of archaeological data. This network is based on an unsupervised learning strategy, that itself finds the similarities between all samples studied.

The network Self-Organizing Maps (SOMs) have been recognized as useful tools for classification of images. This model is based on an un-supervised learning strategy that does not require any previous test samples. The basic idea of this model is to incorporate, in the competitive learning rule, some sensitivity degree related to the neighbourhood or history.

This provides a way of preventing "non-learning" neurons during the training process and, in addition, it favours certain topological proper-ties that must be kept in order to get correspondences between the characteristics of the input patterns [20].

The main objective of the Self-Organizing Map developed by Kohonen is the transformation of a n-dimensional signal or input pat-tern into a discrete multi-dimensional map, and the adaptive development of this transformation according to some topological ordination criterion.

In the last years, an important number of studies involving SOM neural network and image processing, or archaeological remains classification has been carried out.

Evangelou et al., have presented a method to use SOM neural net-work in the study of airborne images, in order to improve Remote Sensing analysis. In that study, the network was used for data mining and knowledge discovery in some images of river Thames area, in United Kingdom. From this study is deduced that SOM is a fast and well-established system of getting land information [21].

The study developed by the University of Wisconsin-Madison [22] has used SOM neural network in the detection of roads portrayed on airborne images.

On the other hand, the Self-Organizing Map has also been used in archaeological analysis. As a specific application, a study was carried out during year 1,999 in order to classify ancient Roman glazed ceramics. The SOM neural network was useful for pattern recognition, and it al-lowed the classification of the ceramics spectra without any previous in-formation [23].

The goal of this paper is to use one Self-Organizing Map on airborne photographs, and to see that it is able to detect automatically roads and ruins in Cáparra archaeological site (in example, the ancient road Ruta de la Plata, or the Roman theatre).

The topology of the SOM used to perform the automated detection of the ancient road Ruta de la Plata and the Roman theatre, allows each output neuron, through the adaptable weight vectors, to process the information from the input linear neurons layer corresponding to a n-dimensional input pattern x.

The neural model consists of N input neurons and M output neurons, where M is the number of classes or prototypes to be extracted by the network, and must be carefully selected according to image complexity and other metrics [20]. A set of feedforward connections from the input to the output layer, with a set of associated weights (WMxN) are used to perform feature detection. In the output layer, self-feedback and lateral connections produce effects depending on the distance from the winning neuron.

The network processing is given by two different stages: clustering and training. In the clustering step, the feedforward connections project input patterns on the feature space and the Euclidean distance is used to identify a winning neuron. In the training step, lateral and self-feedback connections produce excitatory or inhibitory effects depending on the distance to the winning neuron [17]. It is important to emphasize that the weights associated to feedforward connections will contain image prototypes after a training phase has been realised.

For the training process we use a typical SOM training algorithm [20]with the following characteristics:

The fist step consist of weights initialisation. We choose 0.5 value for the initial weight vectors wi (0), (i = 1,2,...,M). Then the input patterns are chosen. We randomly choose a pixel x belonging to the image. After that comes the winning neuron determination. To find the best-matching (winning) neuron i* at time t, we use a minimum-distance criterion:

$$i^*[\boldsymbol{x}] = \min_{1 \le j \le M} \left\| \boldsymbol{x} - \boldsymbol{w}_j \right\|^2 \quad (1)$$

When the calculations finish, we proceed to the weight adjustment. Then, the winning and the other neighbourhood neurons adapt their weights closer to the input vector at each learning step using the expression (2), where α(t) and σ(t) are respectively the learning and neighbouring decreasing at the time functions. The winning neuron's weights are modified proportionally to the learning rate. The weights of neurons in its neighbourhood are modified proportionally to half the learning rate

$$w_i(t+1) = w_i(t) + \alpha(t)\sigma(t)\left(x^n - w_i(t)\right) \qquad to \quad i \in Neighbouring_{i*} \quad (2)$$

The stop criteria for the SOM training algorithm is the achievement of a pre-determined number of iterations (t) is achieved. In order to describe the a(t) and s(t) is necessary to take in account that the learning rate and the neighbourhood are altered during training through two phases:

The first phase is called Ordering Phase. It lasts for a certain number of steps. The neighbourhood distance starts as the map size, and decreases slowly. The learning rate starts at the ordering phase learning rate and decreases until it reaches the tuning-phase learning rate. As the neighbourhood distance and learning rate decrease over this phase, the neurons of the network typically order themselves in the input space with the same topology in which they are ordered physically. Then the algorithm enter the Tuning Phase. This phase lasts for the rest of the training steps. The neighbourhood distance reaches the value 1. The learning rate continues to decrease from the tuning phase learning rate, but very slowly. The small neighbourhood and slowly decreasing learning rate fine tune the network, while keeping the ordering learned in the previous phase stable.

5. PREVIOUS RESULTS

Airborne analysis is a powerful tool for the study of archaeological sites. The archaeological remains, on the other hand, change through time, and some buildings or placements can be altered when many years pass, leaving only their pictures after they disappear. This is the reason why the existence of a method for simple photographs analysis is very important. Thanks to SOM neural network, the basic information contained in a greyscale image can be used as a study parameter, and their pixels are a valid input for its processing.

Although a human expert might interpret the neural network results, these outputs can reveal hidden information, detect slopes and classify the colour intensity with a better precision than human eye, together with the possibility of creating classes and arranging the information depending on the number of output neurons.

The main aim of this study was the detection of three important areas in Cáparra archaeological site, corresponding to the Roman amphitheatre, the ancient road iter ab Emerita Asturicam, nowadays known as Vía de la Plata, and the places where the Ruta de la Plata does not follow the modern roads.

The Roman road known as Vía de la Plata was studied in the photograph taken in year 1,956. Figure number 2 represents the network classification of the image, it found a straight line that crosses the photograph; this line, belonging to the Roman road, is framed in the figure with a box.

Evergreen oaks covered the Roman amphitheatre in year 1,956, so it could not be clearly seen in the photographs. But in year 1,987 the theatre structure was uncovered. So, we used the photograph taken in year 1,987 to study this part of the archaeological site. Figure number 3 shows the results of this experiment, where the SOM network does not detect a full ring of stone (this ring is clearly detected by the human eye), but only half a ring and an irregular circle inside the structure. The reason for this classification is that Cáparra amphitheatre was a very simple and functional building, and it had not a complete wall surrounding the stage, as it happened with other Roman theatres that were more important. Instead of a whole stone wall, the amphitheatre had a wooden *cavea*, and it was evidently eroded and finally disappeared by the action of time.

The parts of the Roman road in which the ancient direction is not followed by new roads are very important. Roman ways were straight, so we tried to reveal the original path of the Ruta de la Plata, despite the modern roads do not follow its route. Using a photograph taken in year 1,987, with a good lightning and not many shadows, the neural network detected the old road direction between the olive trees. Figure number 4 shows the classification results where the remains of a path cross the olive trees following a straight line. This special area is boxed for a better observation.

The above results match with the results of applying ground penetrating radar techniques to the archaeological site.

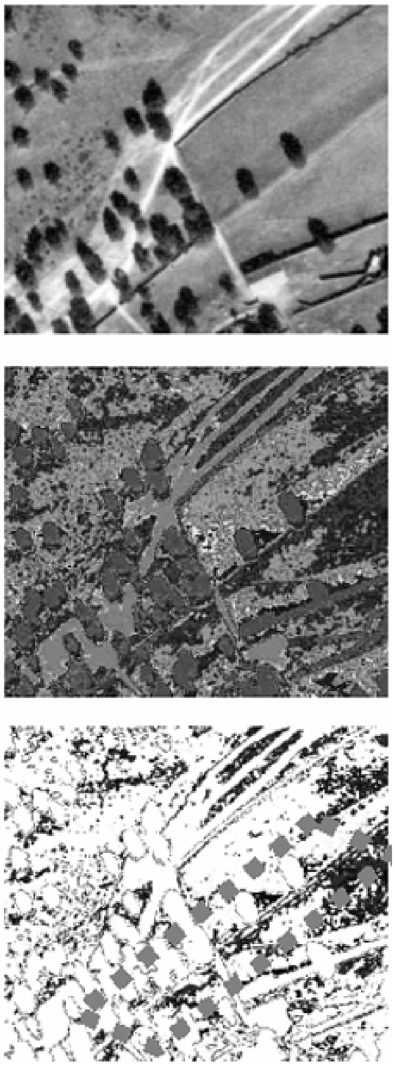

Figure 2.- Test image portraying the Vía de la Plata in year 1,956 (above). SOM result for the detection of the Via de la Plata (middle). The classes that detect the road (below).

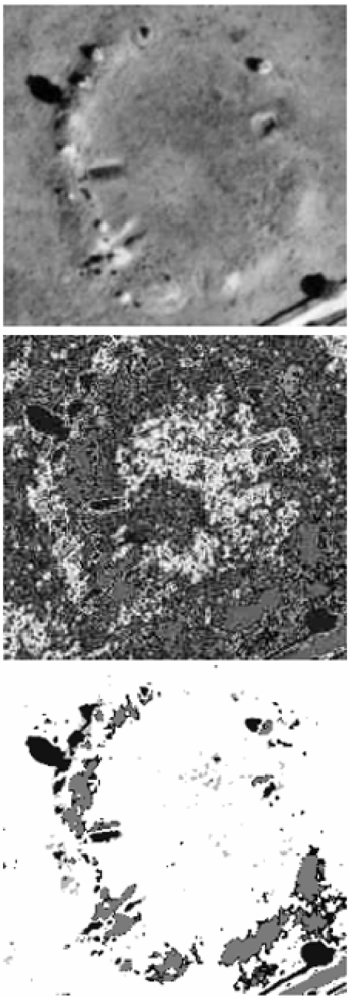

Figure 3.- The test image showing the Roman amphitheatre (above) and the classified image returned b y the SOM (middle). The classes belonging to the amphitheatre (below).

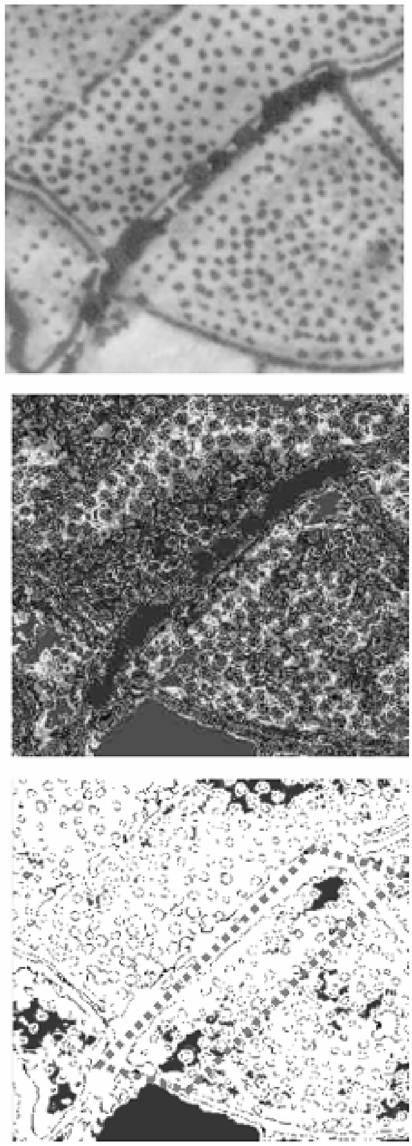

Figure 4.- The test image portraying one of the places where the Roman road does not follow the new road (above). The SOM classified image corresponding to the road (middle). The classes that detect the road between the olive trees (below).

6. FUTURE RESEARCH

The CHRIS instrument offers hyperspectral and multiangular images, which provide us with a very complete information of a scene[24]. On one hand, multiangular images easily help to detect ground elevation and other characteristics of the studies placements. On the other hand, hyperspectral images offer an excellent information about the composition of the elements of a scene. This characteristics are very important for the detection of archaeological sites, as we now explain.

The possibility of detecting the placement of archaeological sites can be deduced by the changes induced on actual ecosystems by our ancestors[25]. The information provided by the site can be very diverse, and it implies nearly every element present in the scene. In the Roman era i.e., rocks, paving and building materials were transported from mines and excavations to the building placement; so if these materials, that differ from the other stones in the scene can be detected, the possibility of finding a site is greatly increased. When it deals with vegetation, plants can offer interesting clues about the soiling, and sites lying under it. The hollows created by earthed buildings, wells or public baths do not allow the growing of plants with deep roots, and sometimes cause terrain elevations as well. So, when it is possible to determine the vegetal species than cover the ground and the ground elevation itself, it is also possible to deduce the existence of hollows, which in turn can lead the archaeological teams to the exact placement of a site.

As it has been shown in this article, and also in other recent investigations[4], [5], [6], [7], [8], remote sensing is a powerful tool for archaeological studies. In addition, neural network processing is a cheap and non-destructive technique to be applied in this area. It is then very expectable that better information provides better results of the processing of images of archaeological sites. Despite the good performance of neural networks, an expert revision of their results would be an ideal complement for the determination of interesting sites. So, the goal of our future studies is to use our background on neural networks, with supervised and non-supervised learning, and the archaeologist knowledge of Cáparra and other sites in Extremadura, to design an expert system able to detect new locations with higher possibilities of being archaeological sites on CHRIS images.

7. SUMMARY AND CONCLUSIONS

The SOM neural network is a good tool for the study and classification of aerial photographs, even when they are very old or despite they are coloured or greyscale images. The network can achieve good results using a small number of input neurons, as it has been demonstrated in this study, in which the main part of the experiments were done using Landsat or even simple photographs as inputs. As it has been shown by the obtained results, the SOM is also capable of finding and detecting the field elevation.

The developed study also allows concluding that artificial neural net-works are very suitable for inter-disciplinary studies, as in this case, in example, where Self Organizing Map has been used for Archaeology purposes. To add more accuracy to the study, the suitability of the neural network has been tested satisfactorily by using ground penetrating radar as a supporting technique.

Neural computation techniques have offered good results when dealing with very simple images, that offer very limited information about the studied scenes. If the characteristics of CHRIS images are introduced, and the algorithms are provided with hyperspectral and multiangular information, it is reasonable to expect an improved performance, and more accurate results in the detection of archaeological areas for future excavations.

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