Automatic Microfossil Detection in Somosaguas Sur paleontologic site (Pozuelo de Alarcón, Madrid, Spain) using Multilayer Perceptrons

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Abstract: - Microvertebrate fossils are used in biochronology to determinate the age of geological layers with a high grade of accuracy, and in paleoecology to extract information about the past enviroment. Actual techniques used to extract microfossils are manual, and require of a high amount of time and human resources. This fact make interesting the study of other more complex techniques. The work presented in this paper evaluates the use of neural networks in order to help in the microfossil extraction tasks, using a high resolution image of the sediment. Color information of the pixels are used to train Multilayer Perceptrons. The analyzed material has been obtained from Somosaguas paleontological site, in Madrid (Spain).

Key-Words: - Multilayer Perceptron, Neyman-Pearson, Microfossil detection, Somosaguas site.

1 Introduction

In this paper we study the use of neural networks applied to microfossil detection. Microfossils are very important in order to establish terrain correlations, allowing to determinate the age of a geological layer with a high grade of accuracy. They are also the fund of any micropaleontological studies.

Actual techniques used to extract microfossils are manual, and require of a high amount of time and human resources. This fact make interesting the study of other more complex techniques, that speed up the extraction of the microfossils, allowing to reduce the required human resources for this task, to increment the volume of analyzed terrain, and, consequently, improving the accuracy of the microfossil studies.

The work presented in this paper evaluates the use of Multilayer Perceptrons in order to help in the microfossil extraction tasks. The analyzed material has been obtained from Somosaguas paleontological site, in Madrid (Spain). Neural networks have been proposed for approximating the Neyman-Pearson detector in different environments. Ruck et al. [1], and Wan [2], demonstrated that a neural network can be used to approximate the optimum bayessian classifier when trained using the mean squared-error criterion. So, due to their capability of approximating the optimum detector, and improving the results in some sense through learning, they can be useful in order to implement an automatic detector.

2 Material and methods

In this section a description of the available data for microfossil detection is carried out. Samples of the used optical photographs are also included, and an explanation about the importance of the different type of microfossil, available in Somosaguas site. After the data description, the main detection problem is formulated, and proposed detection methods are reviewed.

2.1 Microfossil Detection in Somosaguas

Two vertebrate fossil sites, situated in the Universidad Complutense (Pozuelo de Alarcón, Madrid, Spain) have yielded about 600 identifiable rest in different preservation states, belonging to about twenty species of highly diverse sizes, from mastodons to shrews. Their study allows dating at about 14 million of years, and reconstructing an arid climate epoch in the Madrid basin during middle Miocene times, occupied by subtropical woodlands and savannahs with strong floods and without permanent rivers [3].

Somosaguas paleontological site is composed of two different sites, called Somosaguas Norte and Somosaguas Sur. The Somosaguas Norte site contains medium and large fossils., included in a matrix of arkoses. The Somosaguas Sur site is located at the top of a clay layer that contains quartz and feldspar grains, floating next to small and very small fossils of micromammals [4]. Our study is based on the recognition of microvertebrate fossils, so we will focus on the description of the Somosaguas Sur site.

Somosaguas Sur is one of the richest sites in microvertebrates in Madrid. This site has provided hamster rodents (*Megacricetodon collongensis* and

Fahlbuschia darocensis), squirrels (*Heteroxerus grivensis*), dormices (*Armantomys tricristatus*, *Microdyromys koenigswaldi* and *Microdyromys monspeliensis*) lagomorph pikas (*lagopsis penai*), insectivores (*Galerix exilis* and *Miosorex cf. grivensis*) and reptiles (lacertids, anguids and quelonids) [5].

The microvertebrates are not microorganisms but minuscule parts of relatively large organisms, which is the case of rodents, lagomorphs, etc. The microvertebrates study consists on recovering small remains of vertebrates. The most common microvertebrate fossils are teeth and bones. Their sizes are usually of the order of 0,5 mm, so their obtaining techniques are special due to their small size. These techniques are tedious, and require of a high amount of time. Nevertheless, the microvertebrate fossils give a lot of paleontological and geological information, and their study is very important. Based on them, evolutionary, paleoecological and paleoclimatic models can be obtained, and their application in Bioestratigraphy has made them indispensable for geological dating of deposits [6].

The pieces more used in the identification and study of the microvertebrates are the micromammal teeth, long bones of birds and amphibians, and cranial bones of fishes, amphibians and reptiles [6]. In our paleontological site teeth and micromammal bones prevail over the rest.

Teeth are more useful than bones in order to obtain paleontological information, due to:

- They can determine the specie more accurately than bones.
- They provide information about the feeding habits, and therefore about habitat and climatic conditions.

The fragments of bone denominated non identifiable splinters give less information so for this study we will focus on the study of teeth, ignoring the bone fragments. Nevertheless, in a future this method could be also applied to identification of bones and splinters.

The microfossil extraction techniques are special and quite different to macrofossil extraction ones. In first place, several kilograms of sediment are extracted. The quantity of sediment varies in function of the site.

Once extracted the sediment, it is dried to the sun during several hours. Once dried, it is introduced in a recipient with water so the clay is completely dissolved. When the sample is disintegrated the wash sieve process is carried out. This process consists on making the sample go through a series of sieves of different sizes using pressure water. So, several concentrates of mineral grains, bones and teeth are separated from the sediment, and classified in different sizes. In Somosaguas Sur site the proportion of concentrates is about 3.5 Kg over 50 Kg of sediment [5], and the number of microfossils founded in the concentrates is about 1500, giving a ratio lower than 0.8 % (less than 28 g).

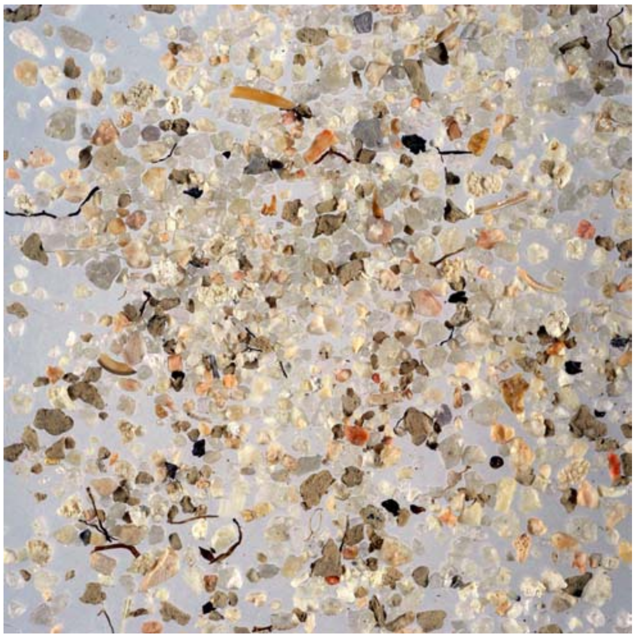

Fig. 1: Photograph of the sample of the concentrate.

The most common technique to separate microfossils from the concentrates is denominated picking. It consists on dividing the concentrate in small fractions for a visual examination and manual separation of the fossils. When grain size is lower than 1 mm, it is necessary the use of binocular magnifying glasses. The picking technique is relatively easy for an expert in microfossils recognition, but however it is quite tedious and requires a lot of time.

In this paper we study the viability of the use of automatic signal processing methods in order to speed up the picking process. This improvement in the picking of the rest could make possible the analysis of a higher volume of sediment, and consequently a higher accuracy in future micro-paleontological studies.

2.2 Descripion of the available data

The data used in this paper is a high definition photography of a sample of a concentrate extracted form Somosaguas Sur site. Figure 1 shows the main photograph of the sampled, used in the experiments.

The average size of the grains is over 2 mm, and the image represents about 6x6 cm of sample (2000x2000 pixels, giving 33.3 pixels per mm). All microfossils have been identified, with special interest over micromammal teeth. A total number of 13 micromammal teeth and 7 fragments of bone have been founded. Figure 2 represent the position of the teeth in the sample.

The seven bone fragments (splinters) are not useful to identify any specie because we only have the central part of long bones, called diaphysis, and there are very few epiphysis (extremes of long bones), which gives us more taxonomic information than diaphysis.

However, dental pieces contain more taxonomic information, allowing to better identify the specie. The 13 dental pieces founded in the sample are:

- Six incisive of continuous growth. This kind of incisive are characteristic of rodents and lagomorphs. The shape of these teeth is lengthened and curved and they are only partially covered with enamel. The waste of this type of teeth can be from 1mm to 1cm per week since they are used to gnaw [7]. So, they never stop growing during the life of the animal. The incisive of continuous growth are abundant in the sample but they give less information than cheek teeth (molars and premolars).
- One first superior left molar (M^1) and two first inferior molars (M_1) of *Megacricetodon collongensis*, a rodent of the *Cricetidae* family.
- One first superior left molar (M^1) and one first inferior molar (M_1) of *Falbuschia darocensis*.
- Two unrecognized dental pieces .

The presence of these species is very important because it allows to determine the biochronology of the Somosaguas site, placing it in the Middle Miocene E biozone (Middle Aragonian) [5].

The input data has been collected using the red, green and blue components of the pixels of the image. For each pixel, a vector **v** has been created using the values of the components of the pixel, and the values of the components of eight neighbors placed at a distance *d*. Figure 3 shows an example of the selection of the neighbors for a distance *d=1* and *d=2*. The value of *d* has been a parameter of the experiments, varying it from 1 to 16 pixels. So, for the highest value of *d* we are considering the color information of nine points uniformly distributed in a 1 mm^2 surface. The output data has been one for the points belonging to a fossil tooth, and zero for the rest, as can be observed in figure 2. So, any possible information of color and texture is used in order to implement the detector.

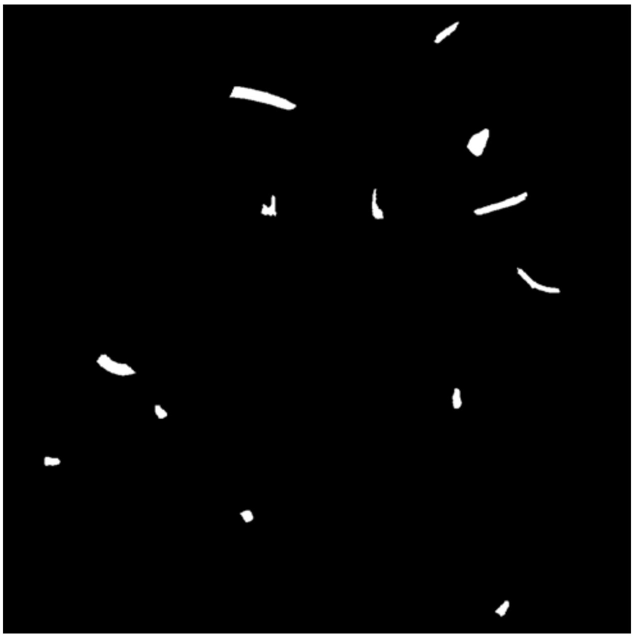

Fig. 2: Fossil teeth of the sample of the concentrate.

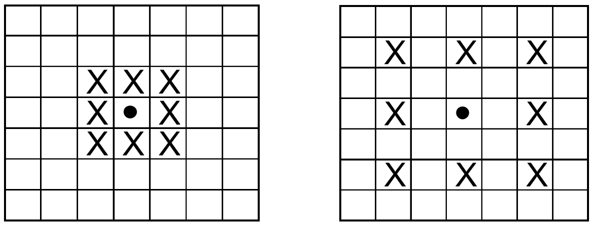

Fig. 3: Examples of the selection of the eight neighbors for a distance *d=1* (left) and *d=2* (right)

The available data have been used to generate three sets of data, which have been used in the experiment: the training set, the validation set and the test set. The training set contains the 4.2 % of the patterns, and is used to train the network. The validation set contains 2.1 % of the total patterns, and is used to early stop the training process. The test set contains the remaining patterns, and it is used to evaluate the detector performance.

2.3 Problem formulation

Automatic microfossil detection can be formulated as a binary hypothesis test: given a set of N observations, the detection system has to decide if they are originated either from a mineral grain (the null hypothesis H_0) or from a fossil tooth (the alternative hypothesis H_1). The objective is to minimize a risk function that is defined as the average cost (1):

$$\overline{C} = \sum_{i=0}^{1}\sum_{j=0}^{1} C_{ij} P(D_i \mid H_j) P(H_j) \tag{1}$$

where $P(D_i|H_j)$ is the probability of deciding H_i when H_j is the true hypothesis, $P(H_j)$ is the prior probability of the hypothesis H_j, and C_{ij} is the cost associated with deciding H_i when the true hypothesis is the hypothesis H_j.

This detector maximizes the probability of detection (P_D), while maintaining the probability of false alarm (P_{FA}) lower than or equal to a specified value. The characteristics of such a detector are reflected in its ROC (Receiver Operating Characteristic) curve, that relates P_D to P_{FA} [8].

This criterion needs the likelihood functions under both, the null and the alternative hypotheses, to be implemented [9][10]. Unfortunately, the designers hardly ever know the likelihood functions. Neural networks (NNs) are proposed as a solution because they can be trained in order to implement radar detectors without prior knowledge of the likelihood functions.

The usage of neural networks to implement radar detectors is also motivated by the demonstration that a feed-forward neural network trained to minimize the mean square error criterion, approximates the Bayes optimal discriminant function [1][2][11]. If the neural network is trained to produce 1 when the feature vector is from class H_1 and 0 when the vector is from class H_0, the discriminant function $g_0(z)$ is given in expression (2), where z is the feature vector, and $P(H_1|z)$ and $P(H_0|z)$ are the a posteriori probability of the classes:

$$g_0(z) = \frac{P(H_1) f(z \mid H_1)}{P(H_1) f(z \mid H_1) + P(H_0) f(z \mid H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \eta \tag{2}$$

$g_0(z)$ can be used to approximate the Neyman-Pearson detector when is compared with a detection threshold, η. When evaluating the generalization capabilities of the MLP, one aspect must be taken into consideration: The detection threshold, η, is necessary to decide if a target is present or not. The P_{FA} is a function of η, and the pairs (P_{FA}, η) must be estimated. This values can be estimated presenting a set of H_0 patterns, and applying the Monte-Carlo simulation.

2.4 Detection using Multilayer Perceptrons

The Perceptron was developed by F. Rosenblatt [12] in 1950 for optical character recognition. The Perceptron has multiple inputs fully connected to an output layer with multiple outputs. Each output is the result of applying the linear combination of the inputs to a non linear function called activation function. Multilayer Perceptrons (MLPs) extend the Perceptron by cascading one or more extra layers of processing elements. These extra layers are called hidden layers, since their elements are not directly connected to the external world. Figure 3 shows a MLP with three inputs, one hidden layer (5 hidden neurons), and six outputs.

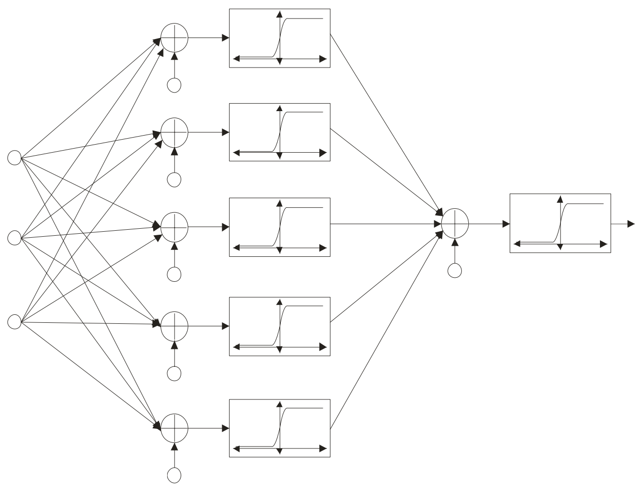

Fig. 3: MLP architecture

Cybenko's theorem [13] states that any continuous function can be approximated with any degree of precision by sigmoidal functions. Therefore we chose a MLP with one hidden layer using the sigmoidal function given in (3) as the activation function.

$$L(x) = \frac{1}{1+\exp(-x)} \tag{3}$$

The MLPs used in this paper have been trained using the Levenberg-Marquardt algorithm [14], and have been regularized using Bayesian regularization [15]. The number of inputs of the network is 27, corresponding to the red, green and blue components of the nine points considered for each pattern. In order to design a detector, the network has one output, which has been thresholded with a value η, calculated for each P_{FA} using Monte-Carlo experiment. The number of hidden neurons is 20.

3 Results of the experiments

Table 1 shows the mean square error measured over the validation set, for the different values of *d* considered in the paper. The error decreases when *d*

Number of neurons	Distance of the neighbors	Mean square validation error
20	d=1	0,03353
20	d=3	0,02722
20	d=4	0,02735
20	d=6	0,02615
20	d=8	0,02221
20	d=10	0,02126
20	d=12	0,01836
20	d=14	0,01980
20	d=16	0,02047

Table 1: Mean square validation error of the networks trained with different *d* values.

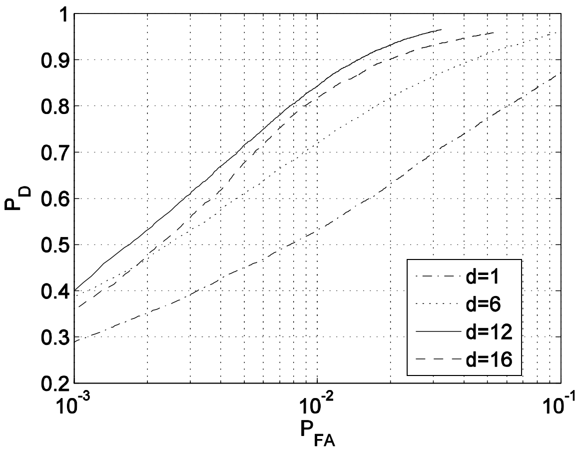

Figure 4: ROC curve for the proposed MLP-based detector.

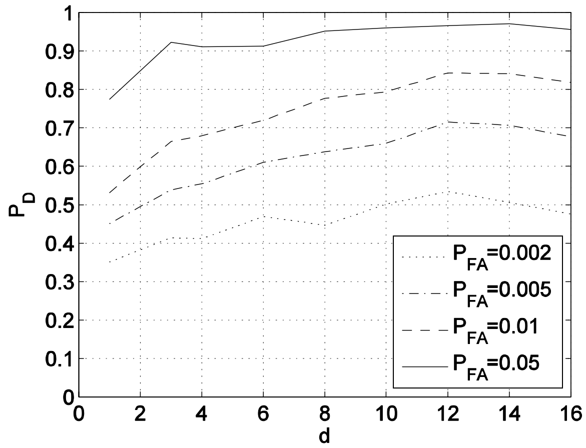

Figure 5: ROC curve for the proposed MLP-based detector.

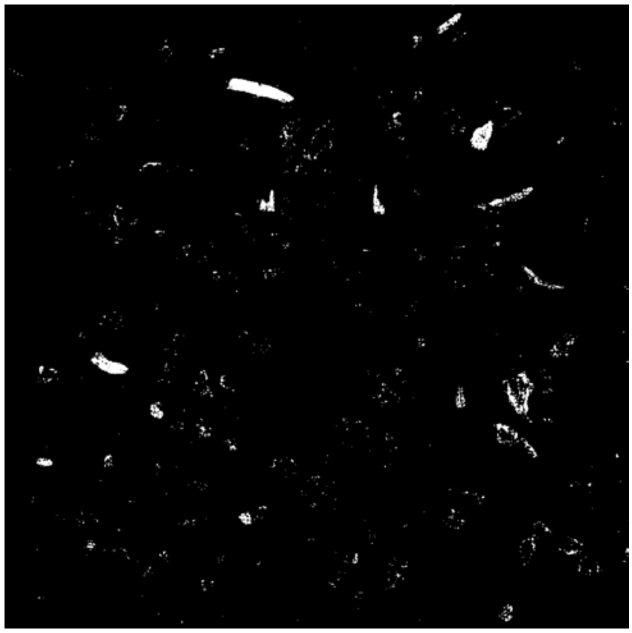

Figure 6: Outputs of the network for the sample of the concentrate, with P_{FA}=5e-3 and P_D=0.715.

increases. The lowest value is obtained with *d=12*. After this value the error increases, due to the size of the grains (about 2 mm, compared with 1 mm of maximum separation of the neighbors with *d=12*).

Figure 4 shows the P_D versus the P_{FA} for four different values of *d*, and figure 5 shows the P_D versus the value of d for four values of P_{FA}. These curves can be used to obtain the grade of accuracy of the method, and they are very interesting in order to establish future comparisons with other methods. Results demonstrate the best value of *d* among the considered is 12.

Figure 6 shows the outputs of the network for the selected sample of the concentrate, with *d=12*, P_{FA}=5e-3 and P_D=0.715. Comparing images in figures 2 and 6, we can observe the grade of learning of the network. Most of the teeth have been clearly identified, and only some small and difficult part of some teeth have not been detected. On the other hand, only a few mineral grains have been identified as teeth by the detector.

4 Conclusion

Microfossils are very important in geological interpretations, but actual microvertebrate extraction techniques are manual and require of a high amount of time and human resources. Actually there are not tools developed for the automation of this process.

In this paper we study the use of neural networks applied to the microfossil detection problem. Color information of a high resolution image has been used to train a MLP. Color information of each pixel and eight neighbors at a distance *d* has been used as inputs of the network. So, not only color but texture information of the fossils has been used to obtain the output.

Results have demonstrate the viability of the proposed method, allowing to improve the visual detection of the micromammal teeth. On the other hand, the use of distanced neighbors has proved to be very beneficial, obtaining the better results with $d=12$.

These results open a future research line, where not only color and texture information but the shape of the objects in the image are used in order to improve the detection of the teeth. Using signal processing techniques, we can design tools in order to improve the accuracy of micropaleontological researches.

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