

IDENTIFICATION OF BEACH FEATURES/PATTERNS THROUGH ARTIFICIAL NEURAL NETWORKS TECHNIQUES USING IKONOS DATA

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ABSTRACT:

Evaluation of beach hydromorphological behavior and classification of beach hydroforms and hydromorphologies is a complex issue. The main objective of this study is to explore pattern recognition methods to identify coastal features/patterns. One of the best known approaches for pattern recognition is artificial neural networks (ANNs). In this study an ANN was applied to an IKONOS image in order to classify the beach features/patterns. Based on the knowledge of the coastal features, five classes were defined. The most common type of ANN used in remote sensing is the multi-layer perceptron (MLP) which was also chosen for this study. The number of nodes in the input layer was determined by the number of input bands – the four IKONOS bands (reflectance values): blue, green, red and NIR. The output layer consisted of five binary nodes, one for each class: Sea, Suspended-Sediments, Breaking-Zone, Beachface and Beach. The ANNs consisted of one hidden layer, with 10 hidden nodes. The dataset was composed by 13775 pixels unequally comprising the five previously mentioned classes. The dataset was randomly divided into training (70% of each class) and validation subsets (30% of each class). Weights connecting the nodes between each layer are initially randomly assigned and adjusted during the learning process in order to minimize the global error. The maximum number of allowed iterations was 300. The ANN that had been trained with the training data was applied to the validation data. The ANN presented a very good performance, demonstrated by the results of the individual class accuracy and overall accuracy (98.6%). The ANN applied in this work have been shown to be useful in the recognition of beach features/patterns.

1. INTRODUCTION

Beach morphological classification was mainly established for Australian and American microtidal sandy environments. Different beach morphologic and classification models were presented by several authors (Wright and Short, 1984; Sunamura, 1988; Lippmann and Holman, 1990; Short and Aagaard, 1993; Masselink and Short, 1993; Masselink and Hegge, 1995; Short 1991, 1999 and 2006) based on wave, tidal and sediment parameters.

Parameters related to wave, tidal and sediments diameter are usually unavailable or nonexistent for the Portuguese coastal zone (Pais-Barbosa, 2007 and Pais-Barbosa *et al.*, 2007). Therefore, without these parameters, the morphologic analysis of high resolution satellite images seems to be a good approach to identify and to classify beach morphologies along the Portuguese coast. Based on this concept, two different approaches were already established in order to identify, measure and classify hydroforms and hydromorphologies.

The first attempt was developed by Pais-Barbosa *et al.* (2007 and 2009). This methodology consisted on the visual analysis of vertical aerial photographs datasets in a Geographical Information System (GIS) environment. However, there are some disadvantages associated to this methodology, such as the time consumption, the subjectivity introduced by the operator, and the impossibility of evaluating the accuracy of this visual analysis.

Teodoro *et al.* (2009) presented a new approach where a pixel-based classification (supervised or unsupervised) and region-based approaches (object-oriented classification) were employed. These results were compared with the visual

identification performed by Pais-Barbosa *et al.* (2007 and 2009), showing a good agreement between the visual identification and the “automatic” classification (Teodoro *et al.*, 2009), as illustrated in Figure 1.

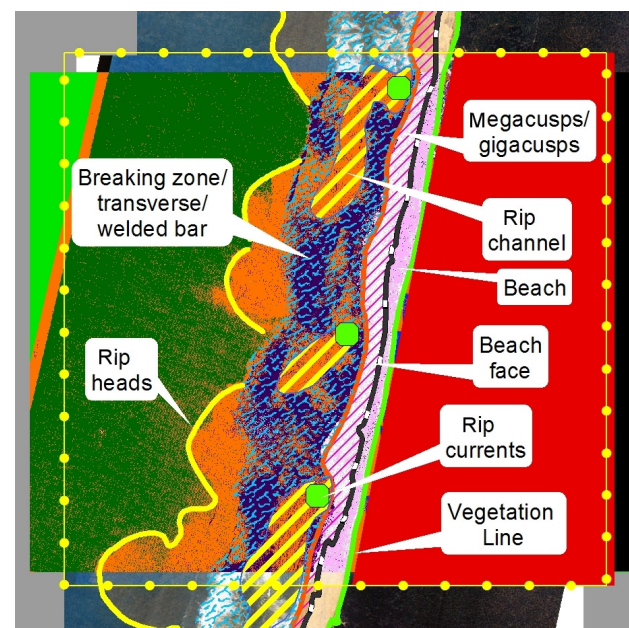


Figure 1. Visual and supervised classifications (parallelepiped classifier) overlapping (Teodoro *et al.*, 2009)

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Satellite remote sensing has revolutionized modern oceanography and coastal applications, providing frequent synoptic-scale information that can be used to deduce ocean/coastal processes. However, it is often difficult to extract interpretable patterns from satellite images, as data sets are large and often non-linear.

A technique that has been applied with success to extract interpretable patterns from different types of data sets is the artificial neural network (ANN). The ANNs have a number of advantages over traditional statistical methods (Wassermann, 1989). Firstly, they can solve non-linear problems of almost infinite complexity (Dayhoff, 1990). Secondly, they are more robust in handling noisy and missing data than traditional methods. This is especially desirable for satellite data from visible and infrared sensors that often have a considerable portion of the image not visible because of clouds. Finally, they do not require prior knowledge and assumptions about the data, such as normality or equality of variances (Chen and Ware, 1999).

There are many examples of the use of ANNs in remote sensing, including many studies that illustrate the ability of ANNs to generalize (Lippmann, 1987; Atkinson and Tatnall, 1997; Wilkinson, 1997). The use of ANNs to classify remotely sensed data has often resulted in a higher or equal mapping accuracy than that achieved with traditional classification methodologies or mixture modeling (Benediktsson *et al.*, 1990; Atkinson *et al.*, 1997; Teodoro *et al.*, 2007). There is considerable interest in the development of a classifier that can be applied to images of coastal areas not only for quantifying water quality parameters (Teodoro *et al.*, 2007) or monitoring protected coastal environments (Palandro *et al.*, 2008), but in many other applications as beach features/patterns classification.

This study focuses on the application of one ANN to an IKONOS image in order to classify the beach features/patterns, in a stretch of the northwest coast of Portugal.

2. METHODOLOGY

The methodology adopted in this work consists in the application of an ANN to an IKONOS image in order to classify the beach features/patterns.

Pais-Barbosa *et al.*, (2007 and 2009) and Teodoro *et al.*, (2009) developed methodologies to identify, to measure and to classify hydroforms and hydromorphologies, based on the visual analysis of vertical aerial photographs datasets in a GIS environment and in image classification techniques, respectively. The hydroforms were identified based on several criteria (location, spectral differences between morphological elements, shape and tide) presented in APPENDIX A. Based on the knowledge of the coastal features, five classes were defined: Sea (S), Suspended-Sediments (SS), Breaking-Zone (BZ), Beachface (BF) and Beach (B).

2.1 Study area

A stretch of the northwest coast of Portugal was chosen as the study area (Figure 2), limited to the north by the Douro River mouth (Vila Nova de Gaia city) and to the south by a small fisherman village (Aguda), with an extension of approximately 9.5 km. This coastal stretch represents a dynamic environment, which is constantly changing in response to natural processes and human activities.

Over the last few years, some coastal erosion in this particular area had been reported (e.g. Southern of Aguda breakwater). The main causes of this serious environmental problem have

been identified as a coastal response to the construction of Aguda breakwater, weakening of the river basin sediment sources and river-sediment transport (Teodoro *et al.*, 2007).

The study area is a rocky coast, with highly dynamic beaches presenting coastal patterns/forms that change continuously. It is composed by very dynamic beach systems, adjusting to wave climate and tide range. The tide regime is semidiurnal (period or cycle of approximately one-half of a tidal day), reaching up to 4.0 m for spring tides (mesotidal coast). The littoral drift has a dominant north–south direction.



Figure 2. Study area (Google Earth®)

2.2 IKONOS data

The IKONOS image (2005/09/18) was acquired under the scope of an ESA funded research project. The IKONOS image was already geometrically corrected. The image bands were calibrated for radiance values (L_λ), through equation (1),

$$L_\lambda = \frac{10^4 * DN_\lambda}{CalCoef_\lambda * Bandwidth_\lambda} \quad (1)$$

where DN_λ is the digital value for spectral band λ , L_λ is the radiance for spectral band λ at the sensor's aperture ($W/m^2/\mu m/sr$), $CalCoef_\lambda$ is the radiometric calibration coefficient [$DN/(mW/cm^2-sr)$] and $Bandwidth_\lambda$ is the band width of spectral band λ (nm).

The surface reflectance (R_λ) was obtained through equation (2),

$$R_\lambda = \frac{\pi * L_\lambda * d^2}{ESUN_\lambda * \cos \theta_\theta} \quad (2)$$

where $ESUN_\lambda$ is the mean solar exoatmospheric irradiances for the spectral band λ , d is the Earth-Sun distance (astronomical units) and θ is the solar zenith angle (degrees). The computed calibration coefficients are listed in Table 1.

Parameter	Spectral band			
	Blue	Green	Red	NIR
Calibration coefficient	728	727	949	843
Band width	71.3	88.6	65.8	95.4
ESUN	1930.9	1854.8	1556.5	1156.9

Table 1. Calibration coefficients for visible and NIR bands of IKONOS image (Thenkabail *et al.*, 2000)

2.3 Training and validation data

As previously mentioned, five classes were defined based on the knowledge of the coastal features: Sea (S), Suspended-Sediments (SS), Breaking-Zone (BZ), Beachface (BF) and Beach (B). The signature separability function must be used to examine the quality of training site and class signature, before performing the classification. The signature separability contains all the available information about signature and information for each class.

Analyzing the transformed divergence values presented in Table 2, only the separability between “Suspended-Sediments” and “Sea” classes is not very good (<1.9).

Class	S	SS	BZ	BF
SS	1.834241			
BZ	2.000000	2.000000		
BF	2.000000	2.000000	2.000000	
B	2.000000	2.000000	2.000000	1.999229

Table 2: Signature separability values (transformed divergence) for the IKONOS image.

The dataset was composed by 13775 pixels unequally comprising the five classes, as presented in Table 3. The dataset was randomly divided into training (70% of each class) and validation subsets (30% of each class).

Class	Training	Validation	Total
S	4133	1771	5904
SS	4091	1754	5845
BZ	329	141	470
BF	88	38	126
B	1001	429	1430
Σ	9642	4133	13775

Table 3. Distribution of the data set into training and validation pixels (number of pixels)

2.4 Artificial Neural Network (ANN)

An ANN is a parallel-distributed processor that resembles the human brain by acquiring knowledge through a learning process, and then stores the knowledge in the connection strength between computational units called neurons. Figure 3 shows a nonlinear model of a neuron. The x_1, \dots, x_m are the input signals, w_{k1}, \dots, w_{km} are the synaptic weights of neuron k , b_k is the bias, v_k is the activation potential of neuron k , $\phi(\cdot)$ is the activation function and y_k is the output signal (Haykin, 1999). An ANN comprises several layers: an input layer, an

output layer and one or more hidden layers between them (Figure 4).

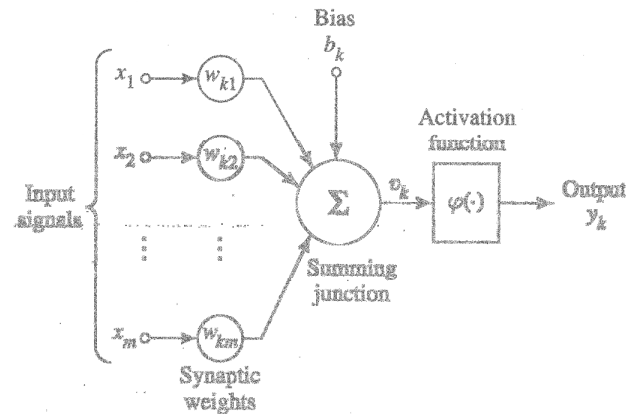


Figure 3. Nonlinear model of a neuron (Haykin, 1999)

The number of nodes in the input layer is determined by the number of input bands, which in this case consisted of four input nodes – the four IKONOS bands: blue, green, red and NIR.

The number of output nodes is dependent upon the number of classes in the classification scheme. In this study, the output layer consisted of five nodes, one for each class: Sea, Suspended-Sediments, Breaking-Zone, Beachface and Beach, as explained in section 2.3.

The hidden layer allows the network to form its own internal representation of the data. If too few nodes are selected, the ANN may not contain sufficient degrees of freedom to form a representation. The ANN implemented consisted of one hidden layer. Networks consisting of more than one hidden layer have not shown significant increases in accuracy compared with those containing just one. Several rules and recommendations exist concerning the calculation of the optimal number of hidden nodes. In this study, the number of hidden nodes was calculated as the number of pairwise separating hyperplanes over the number of classes, according to Dunne and Campbell (1994).

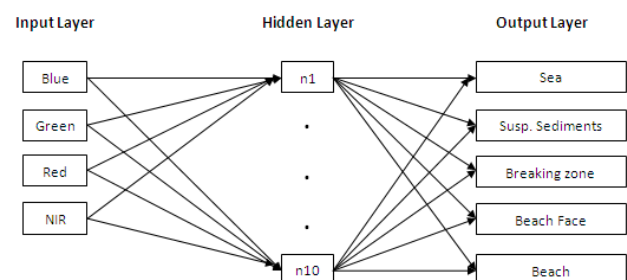


Figure 4. Illustration of the ANN used in this study, consisting of four input nodes, ten hidden nodes (one hidden layer) and five output nodes.

The network performance depends upon the choice of initial weights. Weights connecting the nodes between each layer are initially assigned randomly and adjusted during the learning process to minimize the global error. The weights of the ANN were estimated, using a statistical software (R), based on the Back-Propagation Algorithm (Haykin, 1999). The training process can be stopped according to one of the following user-defined options (Bishop, 1995): after a fixed number of epochs;

after a certain CPU time; when a minimum error function is reached; after minimum gradient is reached and learning per epoch is only marginal; when the error value of validation datasets starts to increase (cross-validation). The highest classification accuracy for the validation data was found when the networks were trained with early stopping (Mehner et al., 2003). The stopping criterion was defined to be the maximum number of allowed iterations, which was defined as 300.

3. RESULTS AND DISCUSSION

In Figure 5, the beach features/patterns map obtained through the application of the developed ANN to the IKONOS image is given, with the discrimination of each identified class.

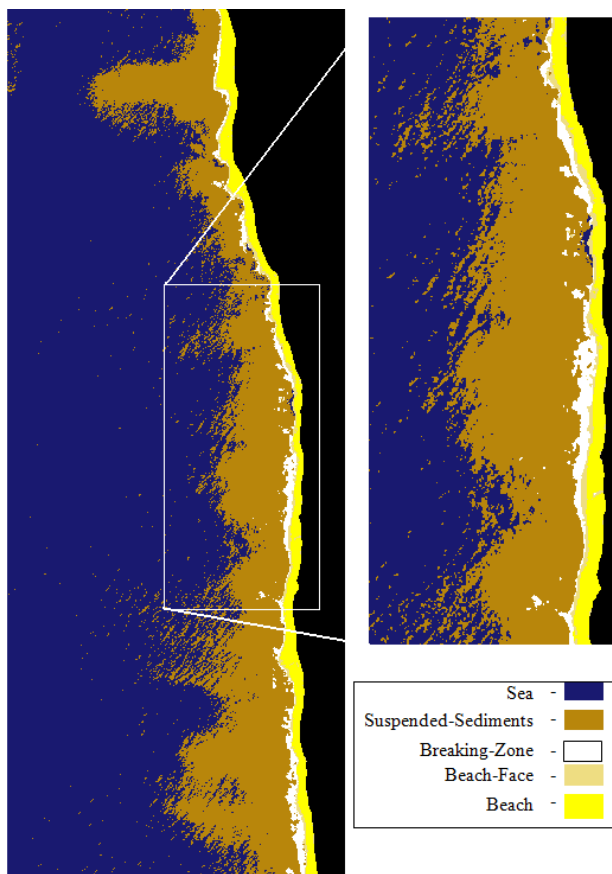


Figure 5. Beach features/patterns map for the IKONOS image, obtained through the implemented ANN.

The network performance was assessed by estimating the accuracy with which the validation data were classified. The ANN presented a very good performance, demonstrated by the results of the individual class accuracy (Table 4) and overall accuracy (98.6%).

Class	S	SS	BZ	BF	B	Accuracy (%)
S	1748	23	0	0	0	98.7
SS	27	1727	0	0	0	98.5
BZ	0	2	139	0	0	98.6
BF	0	1	0	35	2	92.1
B	0	0	0	2	427	99.5

Table 4. Individual class accuracy

This approach conducted to better results than the traditional classification methodologies. For instance, for the same dataset, the best result for the supervised classifications was achieved with the parallelepiped classifier, with a value of 97.5% for overall accuracy. The better result using an objected-oriented approach was found for the pan-sharpened true color imagery with an overall accuracy of 65.8%.

4. CONCLUSIONS

The ANN presented a very good performance, demonstrated by the results of the individual class accuracy and overall accuracy (98.6%). The ANN applied in this work have been shown to be useful in the recognition of beach features/patterns. Given the results obtained, some conclusions can be drawn:

1. The spatial resolution of the IKONOS image suggests that it is adequate for the identification of the considered beach features/patterns, through ANN techniques.
2. The use of ANNs for beach classification from remotely sensed data resulted in an increased classification accuracy when compared with traditional classification methods.
3. When applied to the validation dataset, ANNs performed successfully, with high classification accuracies observed. This fact justifies the future application of this methodology for others locations.

In the future, we are interested in the recent developments in classifier design with the introduction of the support vector machine classifier.

In conclusion, the ANN's have been shown to be useful in the recognition of beach features/patterns.

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APPENDIX A**BEACH FEATURES/PATTERNS IDENTIFICATION CRITERIA**

(Adapted from Pais-Barbosa (2007))

Identification criteria				
Hydroform	Location	Spectral differences between morphological elements	Shape	Tide
Beach	Between dune feet and beachface	Vegetation, dry sand and wet sand	Homogenous land stripe parallel to the coastline	- -
Beachface	Between beach and breaking zone	Dry sand, wet sand and breaking zone	Homogenous land stripe parallel to the coastline	High tide – neap tide
Breaking Zone	Between beachface and sea and/or Suspended Sediments zone	Breaking zone (white), suspended sediments (light brown) and sea (deep-blue); Breaking zone (white) and transverse or alongshore channel (blue);	Alongshore, Crescentic, Transverse welded to land	High tide – neap tide
Suspended Sediments	Between breaking zone and sea	Breaking zone (white), suspended sediments (light brown) and sea (deep-blue);	Irregular alongshore stripe	High tide – neap tide
Sea	Offshore	Deep blue	Homogenous	