A Support System for Fisheries Based on Neural Networks

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Abstract. This paper presents the foundations of a decision support system for the localisation of fisheries based on AI techniques. The purpose of such a system is to reduce the costs of fishing fleets without endangering the sustainable development of the natural resources. Our data sources are satellite images (OrbView-2, Series NOAA, Topex/Poseidon), as well as real catch data obtained from the fishing log of a pilot boat. We have compared neural networks, ANFIS, and functional networks, and we have exported the results to a SIG. The best results were obtained for a perceptron trained with the Backpropagation method.

1 Introduction

In spite of the fact that the exploitation of marine resources is one of the main economic activities in Spain, recent ecological disasters, quota policies and biological stops have started to endanger this important sector. An economic activity that is as competitive as fishing should learn to apply, within a framework of sustainable development [1], new technologies such as decision support systems.

Remote sensors are a vital source of information for this type of system. Our proposal is to use Artificial Intelligence techniques to relate the information that proceeds from Orb View-2, series NOAA and Topex-Poseidon images on the one hand, and the capture data on the other hand. Real capture data, provided by a collaborating boat dedicated to line fishing in the northern Atlantic Ocean, and the information from remote sensors, allow us to create a training and validation set with which to compare the results of various predictors that are generally based on connectionist systems. Valid parameters for our prediction algorithms will allow the boats to find the best fishing zones, reduce search times for fishing grounds, and increase the catches within the existing legal boundaries.

2 Methods and data sources

This section explains the foundations of a new support system for fisheries, which uses the data obtained by various remote sensors and the fishing log of a collaborating boat to predict catches of a the Prionace Glauca, a pelagic shark species that is also known as blue shark or quenlla (see [2]). The main advantages of good prediction are less fuel expenses and less time spent at sea, which will result in a positive effect of

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the involved fleets. The developed system can be extended to any marine species for which we dispose of enough available data to train the system.

Figure 1 shows that the system can be decomposed into three different phases, whose final purpose is to transmit products that can be sent to the embarked units.

The main purpose of phase 1 is to receive the information from various satellites. The system consists of an antenna park that captures signals from the NOAA (in low and high resolution), OrbView-2 (images of the SeaWifs sensor) and Meteosat satellites. The data are stored in a *backup* system and distributed to all the computers that constitute the local network. All these computers have access to the data in order to visualize and process them. An exhaustive description of this phase can be found in [1], [2], [3].

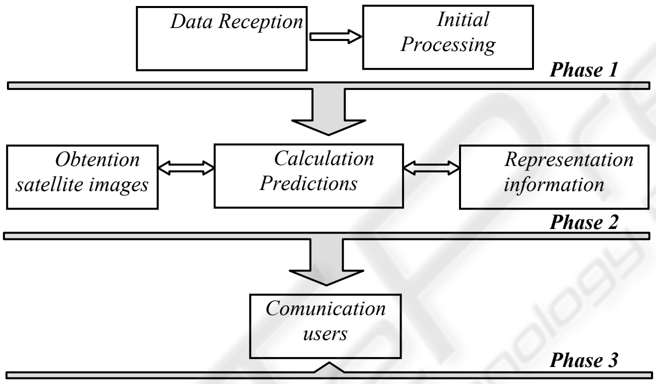

Fig. 1. Chart of the Support System for fisheries

The purpose of this work is to use the data that result from phase 1 to elaborate phase 2:

- Apply digital processing techniques to the initial products in order to obtain new data with biological meaning, e.g. the following high-pass filters which can detect the existence of thermic fronts:
  - DoG (see [4]).
  - Cluster-Shade (see [5]).
- Visualize this information regardless of the used platform.
- Study the sensibility and correlation of the initial data through:
  - The analysis of the main components.
  - Kohonen's Self-Organising Maps.
- Calculate the probability of fishing catches according to environmental parameters obtained through teledetection. We try the following techniques:
  - Networks trained with the backpropagation algorithm.
  - Radial Basis Function networks.
  - Functional networks.
  - Neuro-diffuse inference system (ANFIS)
- Manage all the information efficiently and with a centralized control. To this effect, we design an appropriate database based on the E-R model.

During *phase 3*, our system communicates with the users. The information can be transmitted to the embarked unit by various communication services such as the Inmarsat satellite, a global network that provides a large variety of services (telephone, data, fax, web,…) and is used by many boats for maritime emergency calls. Thanks to the TUNAFIS 4.2 software, developed by other members of the *Instituto de Investigacións Tecnolóxicas*, the users can also send e-mails, manage user accounts and transfer the information into a graphic interface.

2.1 Data sources

This work is based on images of the NOAA, OrbView-2 and Topex-Poseidon series. After an initial processing, the input data are the following:

- Surface Temperature or SST (NOAA)
- Thermic Anomaly (NOAA)
- Thermic front (NOAA)
- Superficial chlorophyll concentration (OrbView-2)
- Altimetric Anomaly (Topex-Poseidon)

We eliminated the thermic anomaly, because a sensibility study with Kohonen networks led to the conclusion that the thermic anomaly does not provide relevant information, probably because it is redundant with the STT.

Apart from these satellite images, we also dispose of the field data of a collaborating fishing boat, that uses the palangre method and transmits the initial and final geographic data of the lance de palangre, and the daily catches for each species during the years 1998 and 1999.

Our training set therefore consists of four inputs from remote sensors images, and one output, which is the number of catches of a determined marine species.

2.2 Methods

The absence of mathematical models and a clear set of knowledge rules, as well as the existence of a set of training data, leads to the use of connectionist systems within the different Artificial intelligence techniques.

2.2.1 Neural Networks

Neural networks have come a far way since the first publications, but they are recognized as a versatile discipline with profound roots in neurosciences, psychology, mathematics, physics, and engineering.

Previous works have confirmed neural networks as an adequate methodology with reliable results:

- *T. Komatsu et al* [6] have predicted sardine catches through NN. They used synaptic weights to analyse the most important physical or biological factor and obtained satisfactory results. Previous regression models did not result effective due to the correlation between the input variables.

- *D. Aurelle et al* [7] used a perceptron with 3 layers and 2 neurons in the hidden layer, and trained with the error bacpropagation algorithm, to predict fishing data.

- *M. J. Dreyfus-Leon* [8] predicted the behaviour of a fisherman with neural networks.
- *Aussem and Hill* [9] predicted the presence of a maligne green alga (Caulerpa taxifolia) through a multilayer perceptron with supervised training.
- *Brosse et al* [10] predicted the abundance of fishing grounds in lakes with neural networks. They compared NN with the Multiple Linear Regression technique and with an analysis of the main components, and concluded that the NN provide the most exact predictions.
- *Maas et al* [11] predict environmental parameters based on temporal series that correspond to the El Niño phenomenon.

An Artificial Neural Network can generally be defined as a machine that is designed to imitate the way in which the human brain performs a task or a function; the neural network is usually implemented with electronic components or simulated by a computer. The results are obtained by using massive interconnections between simple processing elements called neurons.

2.2.2 Functional networks

Functional networks are among the tested algorithms. Since they constitute a relatively recent paradigm, we briefly explain their functioning.

The mid-eighties saw the appearance of extensions of neural networks, such as networks of a high order, probabilistic neural networks [12], and neural networks based on "wavelets" [13]. These models however still acted as mere black boxes without considering the functional structure and the properties of the object that was being modeled. An essential characteristic of the functional networks is the possibility to consider functional restrictions that are determined by the properties of the model. These restrictions lead to a determined topology of the network and therefore to a system of functional equations.

Castillo et al [14] introduced the functional equations as an extension of the neural networks. In a simple but rigourous definition, a *Functional Network* can be described as a Neural Network in which the weights of the neurons are replaced by a set of functions. They present, among others, the following advantages [15]:

1) Contrary to neural networks, functional networks can reproduce certain physical properties that naturally conduct to the corresponding network as long as they can use an expression with a physical meaning in the functions base. In our case we do not dispose of this information and can therefore not make use of this advantage.

2) The network parameters can be estimated by solving a linear equations system, a rapid and unique solution that is the global minimum of the error function.

Functional networks have been applied successfully to problems of medical diagnosis and to conjugated Bayesian distributions. These problems, the solutions based on functional networks, and the formalisms of the equations and functional networks, can be found in the book by Castillo et al [15].

A functional network consists of the following elements:

1) *An input layer of storage units*. This layer contains the input data.
2) *An output layer of storage units.* This layer contains the output data.
3) *One or various layers of processing units.* These units evaluate a set of input values that proceed from the previous layer (an intermediate unit or the input layer), and calculate values that will be considered in the following layer. Each neuron is associated to a functional neuron that can possess several arguments or inputs; this allows us to introduce part into each processing unit part of the mathematical model that helps to explain our problem.
4) *None, one or various layers of intermediate storage units.* These layers contain units that store intermediate information produced by the neural units, and as such allow us to force the coincidence of the outputs of the processing units.
5) *A set of directed links.* They connect input links or intermediate layers to neural units, and neural units to intermediate or output units.

2.2.2.1 Implemented Functional Network

We have adapted the *separability* model explained in [15] to our problem. The topology of the proposed network for the prediction of Prionace Glauca catches appears in Figure 2.

In this model, the two functions families are known: $\{f_i \mid i=1,\dots,r\}$ and $\{g_j \mid i=1,\dots,k\text{-}r\}$, and output Q can be calculated as follows:

$$Q=\sum_{i=1}^{r}\sum_{j=1}^{k-r}c_{ij}f_i(x)g_j(y)+\sum_{i=1}^{r}\sum_{j=1}^{k-r}d_{ij}f_i(z)g_j(v) \qquad \textbf{(1)}$$

We must therefore calculate the adequate coefficients c_{ij} and d_{ij}, based on the training set that was already used for the neural networks. The learning process of our network can be described as follows:

The error e_k of each pattern is defined as:

$$e_k=x_{0k}-Q=x_{0k}-\sum_{i=1}^{r}\sum_{j=1}^{k-r}c_{ij}f_i(x_k)g_j(y_k)+\sum_{i=1}^{r}\sum_{j=1}^{k-r}d_{ij}f_i(z_k)g_j(v_k) \qquad \textbf{(2)}$$

The final purpose of our training is to minimize the sum of the errors of all the patterns, i.e., minimize E:

$$E=\sum_{k=1}^{n}e_k^2 \quad \text{where n is the number of patterns of the training set} \qquad \textbf{(3)}$$

According to the method of square minima, the patterns set that minimizes E must be the solution of the following equations system:

$$\begin{cases} \dfrac{\partial E}{\partial c_{pq}} = 2\sum_{k=1}^{n} e_k f_p(x_k) g_q(y_k) = 0 \\ \dfrac{\partial E}{\partial d_{pq}} = 2\sum_{k=1}^{n} e_k f_p(z_k) g_q(v_k) = 0 \end{cases} \qquad \text{with p=1,…,r;} \quad \text{q=1,…,r-s} \tag{4}$$

If we replace e_k by expression (2), we obtain the following equations system:

$$\begin{cases} \dfrac{\partial E}{\partial c_{pq}} = 2\sum_{k=1}^{n}\left(\sum_{i=1}^{r}\sum_{j=1}^{k-r} c_{ij} f_i(x_k) g_j(y_k) + \sum_{i=1}^{r}\sum_{j=1}^{k-r} d_{ij} f_i(z_k) g_j(v_k) \right) e_k f_p(x_k) g_q(y_k) = 0 \\ \dfrac{\partial E}{\partial d_{pq}} = 2\sum_{k=1}^{n}\left(\sum_{i=1}^{r}\sum_{j=1}^{k-r} c_{ij} f_i(x_k) g_j(y_k) + \sum_{i=1}^{r}\sum_{j=1}^{k-r} d_{ij} f_i(z_k) g_j(v_k) \right) e_k f_p(z_k) g_q(v_k) = 0 \end{cases} \tag{5}$$

with p=1,…,r; q=1,…,r-s

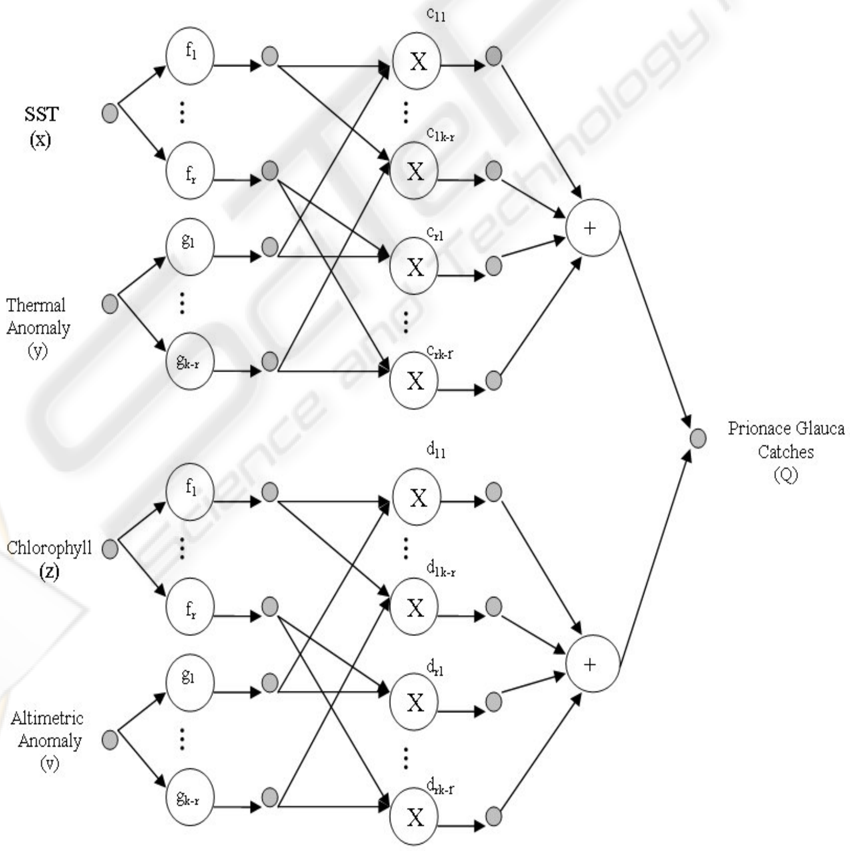

Fig. 2. Functional network based on the proposed separability model for capture prediction.

In order to obtain comparable results, we use the same training patterns as those used to train the neural networks of the previous section. Functional networks are especially appropriate for problems with mathematical models. In our case, where there is no model, we opt for the elementary polynomic family to resolve the system.

We have carried out tests with the following functions families:

- *Case 1*: $\{f_i\}=\{1,x,x^2,x^3\}$ and $\{g_i\}=\{x,x^2,x^3,x^4\}$.
- *Case 2*: $\{f_i\}=\{1,x,x^2,x^3,x^4\}$ and $\{g_i\}=\{x,x^2,x^3,x^4,x^5\}$.
- *Case 3*: $\{f_i\}=\{1,x,x^2,x^3,x^4,x^5\}$ and $\{g_i\}=\{x,x^2,x^3,x^4,x^5,x^6\}$.

We must be especially cautious when selecting the functions families, because the determinant of the coefficients matrix could have two identical columns. This is why the family $\{g_i\}$ does not contain the elemental function "1".

2.2.3 ANFIS

We have implemented ANFIS type 3 systems (Takagi-Sugeno) [16][17], using the already used patterns for neural and functional networks as training and validation sets, and searching the best topology for our system. We have defined various ANFIS [17] for the different tests, and the best results were obtained by the system that had 2 membership level functions for each variable. The output is of the order 0 (constant function).

Figure 3 shows the topology:

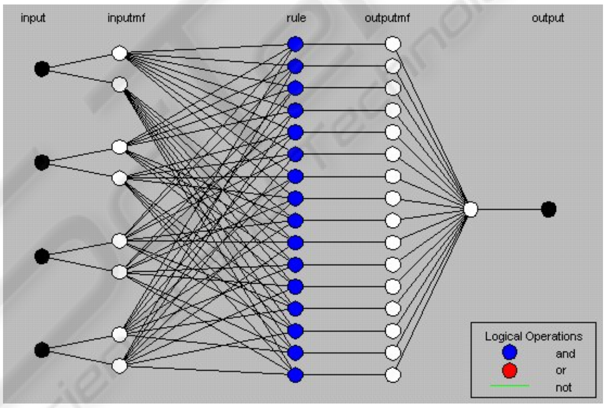

Fig. 3. Topology of the ANFIS system of *case 1*, in which for each input variable there are only two characteristic functions (membership functions, MF).

3 Results

3.1 Comparing results

We have used 4 input variables (SST, Heating-Cooling, chlorophyll concentration, and altimetry) and one output variable (Quenlla catches) to create a multilayer perceptron trained with an error Backpropagation algorithm [18] [19].

Our purpose was to find the simplest network that allows us to draw conclusions on the conditions that maximize the catches of the embarked unit. After training the network, we noticed that the number of neurons of the hidden layer hardly affects the error presented by the network. There are small initial differences that may be due to the arbitrary initialization of the network's weights. In all the cases, the MSE of the training set remains close to 0.01, whereas the error of the validation set is slightly below 0.02.

These results point towards the simplest network, i.e. the network with 2 neurons in its hidden layer. Figure 4 shows the mean square errors of the training and validation set of other modern paradigms in AI, the functional networks [15], and the neuro-diffuse system ANFIS [17]:

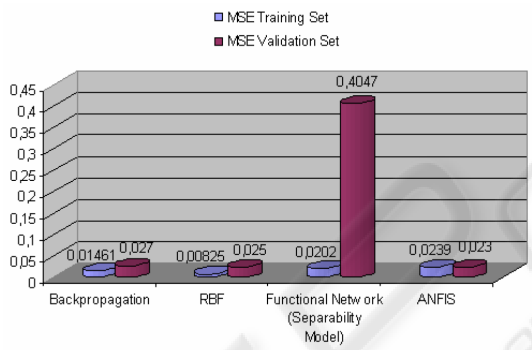

Fig. 4. MSE of the training and validation sets in 4 tested algorithms.

If we want the studied algorithm to be a good predictor, we must obtain a low error for the training and validation set. We created this validation set with field data that we are not used during training. This validation set contains a representative number of all the patron types of the field data. A validation error that is considerably bigger than a training error indicates a case of over-adjustment or over-training. It is well known that when we use a model with many parameters to adjust a dataset that proceeds from a process with a small degree of liberty, the obtained model may not discover the real tendencies of the original process, even though it may present only a small data adjustment error. In this case, the training is limited to the interpolation of the data, including the noise, by means of a complicated sigmoid function.

Figure 4 shows the best results after training the different neural, functional and ANFIS networks, and avoiding all the cases that presented over-adjustment. The errors of Figure 4 are all of the same order, except the validation error of the functional network. This means that the generalization capacity of this algorithm is smaller for our particular case, due to the inexistence of a mathematical model that is able to explain the problem [20].

Finally, the system was implemented with the multilayer perceptron trained with a Backpropagation algorithm, which is simpler than the ANFIS and the RBF network.

The Backpropagation network can now be applied to calculate the probability map of Prionace Glauca catches. The network inputs are the values of the pixels of each image; the input that corresponds to the altimetric anomaly is the value (not zero) that is closest to the pixel, if it does not already exist. We use the network output to generate a fishing probability map that can be exported to a SIG (see Figure 5). The high grey levels (clear colours) indicate a high fishing probability.

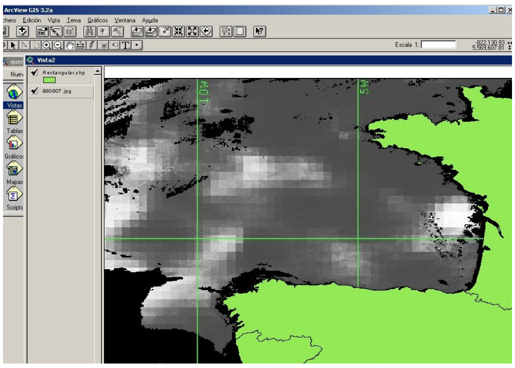

Fig. 5. Probability map of Prionace Glauca catches on 7-8-1998, obtained through a neural network trained with a Backpropagation algorithm. High grey levels (clear colours) indicate a high fishing probability

4 Conclusions

- ✓ We have elaborated a decision support system for the operational exploitation of fisheries by integrating various Artificial Intelligence techniques into a data acquisition system with data from remote sensors.

- ✓ Based on the images of two entire years (1998 and 1999) and on field data, we have generated an extensive information system that includes a relational database with environmental parameters, geographical coordinates and catches.

- ✓ We have used the previously mentioned information system to design a decision support system. Our problem is characterised by the absence of global and local models, the inexistence of a knowledge base, and by variables that are poorly interrelated (except for the anomalies and the thermic fronts). These factors have led to the use of algorithms of the connectionist tendency within the Artificial Intelligence field.

- ✓ We have designed several tools that are able to predict the optimal fishing grounds according to the information of a series of satellites. The obtained results were validated with patterns that differ from those that were used for the training.

- ✓ In order to develop the necessary applications to integrate the neural network into the digital treatment of images, we had to previously unify the different image formats for each satellite. The output of the system consists in a fishing probability map generated from the used network outputs. At the same time, we have implemented applications to access the information system and to calculate punctual predictions. These tools were developed in such a manner that the user of the system disposes of all the utilities in a comfortable and accessible environment.

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