Pattern Recognition in AVHRR Images by Means of Hibryd and Neuro-fuzzy Systems

Jose Antonio Piedra, Francisco Guindos, Alberto Molina, and Manuel Canton

[1] Universidad de Almeria, Departmento de Languajes y Computación,
Phone +34 950 0140 36, 04120 Almeria, Spain
{jpiedra, fguindos, mcanton}@ual.es
alberto@altoalmanzora.org

Abstract. The main goal of this work is to improve the automatic interpretation of ocean satellite images. We present a comparative study of different classifiers: Graphic Expert System (GES), ANN-based Symbolic Processing Element (SPE), Hybrid System (ANN – Radial Base Function & Fuzzy System), Neuro-Fuzzy System and Bayesian Network.. We wish to show the utility of hybrid and neuro-fuzzy system in recongnition of oceanic structures. On the other hand, other objective is the feature selection, which is considered a fundamental step for pattern recognition. This paper reports a study of learning Bayesian Network for feature selection [1] in the recognition of oceanic structures in satellite images.

1 Structure of the Automatic Interpretation System

Fig. 1 depicts the overall structure of the system that has been developed. In a first step, the raw image is processed by means of algorithms such as radiometric correction, map projection and land masking. These are well known techniques also used when the analysis is made by human experts. However, we don't make any image enhancement like histogram equalization or contrast stretching that are appropriate to make some features visible to human eye but have no positive effects when the images are going to be processed by digital systems.

The second step aims to detect clouds pixels that are opaque to radiance data measured in the AVHRR infrared and visible scenes. Cloudy images are distorted in such a way that the zone affected isn't of any value for our later processing, so we build a mask of 0s that will exclude these pixels [2].

The following task is the segmentation that will divide the whole image in regions. The idea is that each phenomenon of interest should coincide with one or a small set of the segmented regions. The nature of ocean dynamics makes very difficult this process that is nevertheless fundamental, so we've designed an iterative knowledge-driven method to perform this part of the process pipeline [3].

The next task is the features or descriptors selection, which consists of selecting an optimal or sub-optimal feature subset from a set of candidate features. The most common framework for features selection is to define some criteria for measuring the goodness of a set of features, and then use a search algorithm to find an optimal or sub-optimal set of features [4]. We have used Bayesian networks for features selection in the recognition of oceanic structures in satellite images [5].

R. Moreno Díaz et al. (Eds.): EUROCAST 2005, LNCS 3643, pp. 373 – 378, 2005.

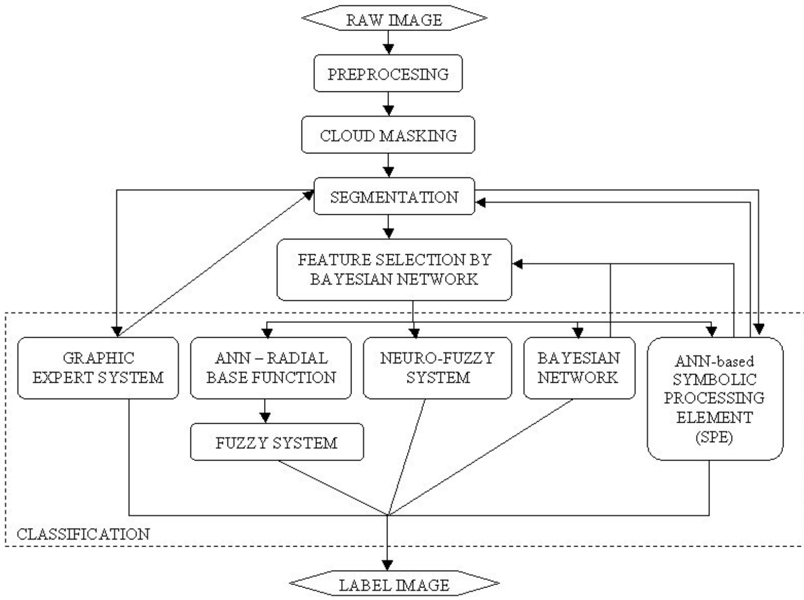

Fig. 1. Structure of the ocean feature recognition system

In the last step, each region produced in the segmentation is analyzed and, if the recognition is positive, it is labeled with the identifier of the matching structure. The structures of interest in the Canary Islands zone as defined in are: coastal upwelling, warm eddies, cold eddies and island wakes. The vast majority of the regions that appear in the segmentation are of no special interest and they are labeled with a 0.

We have implemented a redundant recognition subsystem. It has an ANN-based Symbolic Processing Element (SPE) module [6], a rule-based Graphic E.S. (GES) [3], Bayesian Network, Hybrid System (Artificial Neural Network based Radial Base Function and Fuzzy System based Sugeno) and Neuro-Fuzzy Systems (NEFPROX, ANFIS) performing the same task. The purpose is to test different methodologies and to provide a way to validate and compare these results.

2 Detailed Process

2.1 Feature Selection by Bayesian Network

The most common framework for feature selection is to define criteria for measuring the goodness of a set of features, and then use a search algorithm that finds an optimal or sub-optimal set of features. Our goal in this step is to apply the theory of learning Bayesian Network to the reduction of irrelevant features [1] in the recognition of oceanic structures in satellite images [6].

The experiment was done over the feature set obtained in the work [6]. The learning algorithms (K2, VNSST, Naive-Bayes) have been evaluated with different configurations of parameters to select the best configuration. Table 1 shows the summary of comparative results generated from SPE (Neural Network) and Learning Bayesian Method. This method allows choosing a feature subset obtaining the same accuracy rate (about 80%) that with the initial feature set.

Table 1. Comparative results of feature selection

Algorithms	Number of Features
Symbolic Processing Element	50
K2 Learning	15
VNSST Learning	15
Naive-Bayes Learning	50

2.2 Classification

All classifiers has been designed and tested with the same image data set.

2.2.1 Hybrid System (Artificial Neural Network and Fuzzy System)

Fuzzy modeling is one of the techniques currently being used for modeling nonlinear, uncertain, and complex systems. An important characteristic of fuzzy models is the partitioning of the space of system variables into fuzzy regions using fuzzy sets [7]. One of the aspects that distinguish fuzzy modeling from other black-box approaches like neural nets is that fuzzy models are transparent to interpretation and analysis (to a certain degree).

Radial basis function networks and fuzzy rule systems are functionally equivalent under some conditions. Therefore, the learning algorithms developed in the field of artificial neural networks can be used to adapt the parameters of fuzzy systems. We use the relationship between RBF neural network and fuzzy system for classification purpose [8].

The operation begins training a neuronal network under initial conditions (equivalence with fuzzy system). Neural network obtains a set of rules, that are used to build the fuzzy system. Both systems are used in classification processes.

2.2.2 Neuro-fuzzy System

Neuro-Fuzzy System refers to the combination of fuzzy set theory and neural networks with the advantages of both:

1. Manage imprecise, partial, vague or imperfect information
2. Handle any kind of information (numeric, linguistic, logical, etc.)
3. Self-learning, self-organizing and self-tuning capabilities
4. No need of prior knowledge of relationships of data
5. Reduce human decision making process
6. Fast computation using fuzzy number operations

We use ANFIS [9] (Adaptative Network based Fuzzy Inference System), which is a fuzzy inference system implemented in the framework of adaptative network. ANFIS can serve as a base for constructing a set of fuzzy if-then rules with appropiate membership functions to generate the stipulated input-output pairs.

On the other hand, we use a general approach to function approximation by a neuro-fuzzy model based on supervised learning. NEFPROX [10] (NEuroFuzzyfunction apPROXimator) has a similar structure as the NEFCON model, but it is an extension, because it does not need reinforcement learning. On the other hand it also extends the NEFCLASS model [11], that can only be used for crisp classification tasks.

2.2.3 Bayesian Networks

Bayesian Networks provide an intuitive graphical visualization of the knowledge including the interactions among the various sources of uncertainty. Bayesian Networks are models for representing uncertainty in our knowledge. We use them in feature selection and classification.

3 Results

The information provided by knowledge driven classifiers are refurbished with the original segmentation to create images (Fig. 2) that show in a visual way each the labeled ocean feature of interest. Each feature is represented by different colored region in a map where each color represents one of the ocean phenomena we are looking for.

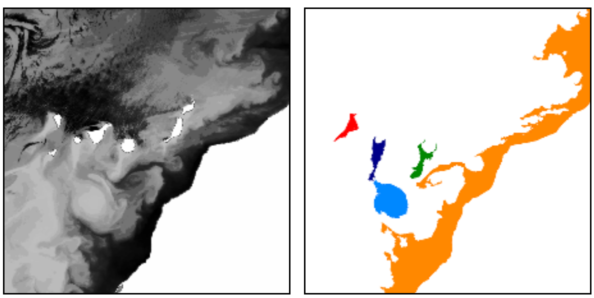

Fig. 2. AVHRR scene (equalized) and feature map (orange:upwelling, red-green-blue: warm wakes,light blue: warm gyre)

Results from systems SPEs,GES, HS, BN and NFS, depend mainly on the quality of the images. In general, a good number of training images are needed. For GES, the

Table 2. Comparative results of classification

Classifier	Accuracy Rate
Hybrid System	60 %
NEFPROX	60 %
ANFIS	60 %
Bayesian Networks (K2,VNSST Learning)	80 %
S.P.E.	80 %
G.E.S.	95 %

best results are achieved when the human expert provides the system with specific knowledge about the target area. When these requisites are met, the systems produce positive ocean structures recognition, which is shown in table 2.

4 Conclusions

We have explored the use of Bayesian networks as a mechanism for feature selection in a system for automatic recognition of ocean satellite images. The use of Bayesian networks has provided benefits with respect to SPE, not only in the reduction of relevant features, but also in discovering the structure of the knowledge, in terms of the conditional independence relations among the variables. In future works we plan to improve the accuracy rate of the system including more variables. Furthermore, we expect to use models to avoid the discretisation of the continuous features when learning Bayesian networks.

On the other hand, obtained results aren´t expected for classification process by hybrid and neuro-fuzzy system. They don´t correspond with results of other cassifiers (EPS, GES and Bayesian Network). The main problem is the number of generated rules, which is excessive. In future works we plan to improve the accuracy rate of the hybrid and neuro-fuzzy systems including more variables, tunning training parameters, optimizing the obtained structure and automating the construction of neurofuzzy system.

Finally, the structure of the automatic interpretation system that has been introduced, it is a complex and independent structure for the following tasks:

1. Iterative segmentation-recognition cycle is made by means of graphic expert system.
2. Feature selection and validation of knowledge is done by bayesian learning
3. Multiple classification allows to find different interpretations of the existing knowledge to validate the knowledge of the classifiers.

Acknowledgments

This work is being partially supported by the Spanish Commission for Science and Technology (CICYT) through the project 2004-TIN-05346.

References

1. Inza I., Larrañaga P., Etxeberria R. and Sierra B.: Feature Subset Selection by Bayesian networks based optimization. Artificial Intelligence, nº 123, (2000) 157–184.
2. Torres J.A., Guindos F., Peralta M. and Cantón M.: An Automatic Cloud-Masking System Using Backpro Neural Nets for AVHRR Scenes, IEEE Transactions On Geoscience and Remote Sensing, vol. 41, nº 4, (2003) 826–831.
3. Guindos F., Piedra J.A. and Cantón M.: Ocean features recognition in AVHRR images by means of bayesian net and expert system, 3rd International Workshop on Pattern Recognition in Remote Sensing, Kingston University, United Kingdom. August (2004).

4. Langley P. and Sage S.: Induction of selective Bayesian classifiers. In Proceedings of the Tenth Conference on Uncertainty in Artificial Intelligence, Seattle. Morgan-Kaufmann, (1994) 399–406.
5. Yamagata Y. and Oguma H.: Bayesian feature selection for classifying multi-temporal SAR and TM Data. IEEE, (1997) 978–980.
6. Torres J.A., Guindos F., López M. and Canton M.: Competitive neural-net-based system for the automatic detection of oceanic mesoscalar structures on AVHRR scenes. IEEE Trans. on Geoscience and Remote Sensing, vol.41, issue 4, April (2003) 845–852.
7. Zadeh L.A.: Fuzzy Logic. IEEE Computer, vol. 21 , issue 4 , April (1988) 83–93.
8. Yaochu Jin, Werner von Seelen, Bernhard Sendhoff: Extracting Interpretable Fuzzy Rules from RBF Neural Networks. Institut für Neuroinformatik, Ruhr-Universität Bochum, FRG. Internal Report (2000–2002).
9. Roger Jang: ANFIS Adaptative Network based Fuzzy Inference System. IEEE Transactions On Systems, Man and Cybernetics, vol 23, nº 3. May/June (1993).
10. Nauck D. and Kruse R.: A neuro-fuzzy approach to obtain interpretable fuzzy systems for function approximation. Fuzzy Systems Proceedings, IEEE World Congress on Computational Intelligence., vol 2 , May (1998) 1106 –1111.
11. Nauck D.: Knowledge discovery with NEFCLASS. Fourth International Conference on Knowledge-Based Intelligent Engineering Systems and Allied Technologies, vol. 1 , 30 August-1 September (2000) 158–161.