PATTERN RECOGNITION IN AVHRR IMAGES BY MEANS OF HIBRYD NEURO-FUZZY SYSTEMS AND FUZZY LATTICE NEUROCOMPUTING MODEL.

Jose Antonio Piedra, Manuel Canton and Francisco Guindos

Universidad de Almeria, Departamento de Lenguajes y Computacion, Phone +34 950 0140 36, 04120 Almeria, Spain {jpiedra, mcanton, fguindos}@ual.es

Extended Abstract

Our goal in this work has been to study methods for the automatic interpretation of ocean satellite images by means of the recognition of meso and macroscalar ocean structures. The difficulty of the image analysis and understanding problem for ocean satellite data is due, in large part, to the lack of a precise mathematical description of the observed structures and to their variability. This work proposes an approximation that show the results obtained with an automatic interpretation system for AVHRR (Advanced Very High Resolution Radiometer) infrared images, developed to detect and to label oceanic structures. This automatic interpretation system contains mainly a set of different classifiers, that allow to compare the results. The classifiers use functional and operational principles derived from the ANNs (Artificial Neural Nets), Rule-Based Knowledge Systems and Fuzzy Systems.

The overall structure of the system is divided in several steps. In a first step, the raw image is processed by means of algorithms such as radiometric correction, map projection and land masking. The second step aims to detect clouds pixels that are opaque to radiance data measured in the AVHRR infrared and visible scenes[1]. The following task is the segmentation that will divide the whole image in 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 [2]. 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 [3], 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][6]. 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 [7] are: coastal upwellings, warm eddies, cold eddies and island wakes.

We have implemented a redundant recognition subsystem. It has an ANN-based Symbolic Processing Element (SPE) module [1], a rule-based Graphic E.S. (GES) [2], Bayesian Network, Hybrid System (Artificial Neural Network based Radial Base Function and Fuzzy System based Sugeno [8]), Neuro-Fuzzy Systems (NEFPROX, ANFIS [9] [10]) and fuzzy lattice neurocomputing (FLN) models [11] performing the

same task. The purpose is to test different methodologies and to provide a way to validate and compare these results.

We have explored the use of Bayesian networks as a mechanism for ocean features selection. 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. Furthermore, we use thecniques to avoid the discretisation of the continuous features during the training of Bayesian networks.

On the other hand, we have used a different hybrid neurofuzzy system that combines fuzzy system and neural networks (ANFIS, NEFCLASS, NEFPROX). The hybrid neurofuzzy system is capable of performing fuzzy reasoning by using the trained fuzzy neural network, which is constructed by learning from data. The results have shown that the neurofuzzy systems are fault tolerant, i.e., it can efficiently be trained from either well-defined initial fuzzy rules or ill-defined initial fuzzy rules; and the efficiency of the learning algorithm can be improved by choosing appropriate membership functions. The classification results are best than other classifiers like EPS, GES and Bayesian Networks, but the problem is the number of generated rules, which is excessive. Other model used is fuzzy lattice neurocomputing (FLN) [11] that allows to simplify the number of fuzzy rule set. FLN has increased visual interpretability of hybrid model and improved classification accuracy.

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