Fuzzy Content-Based Image Retrieval for Oceanic Remote Sensing

Jose A. Piedra-Fernández, Gloria Ortega, James Z. Wang, and Manuel Cantón-Garbín

***Abstract*—The detection of mesoscale oceanic structures, such as upwellings or eddies, from satellite images has significance for marine environmental studies, coastal resource management, and ocean dynamics studies. Nevertheless, there is a lack of tools that allow us to retrieve automatically relevant mesoscale structures from large satellite image databases. This paper focuses on the development and validation of a content-based image retrieval system to classify and retrieve oceanic structures from satellite images. The images were obtained from the National Oceanic and Atmospheric Administration satellite's Advanced Very High Resolution Radiometer sensor. The study area is about W2° − 21°, N19° − 45°. This system conducts labeling and retrieval of the most relevant and typical mesoscale oceanic structures, such as upwellings, eddies, and island wakes located in the Canary Islands area and in the Mediterranean and Cantabrian seas. Our work is based on several soft computing technologies such as fuzzy logic and neurofuzzy systems.**

***Index Terms*—Automatic recognition, fuzzy logic, image retrieval, neurofuzzy system, ocean satellite images, ocean structures.**

I. Introduction

DURING the last decades, there has been a substantial increase in the number of environmental problems that need to manage massive volumes of data (the "big data" problems). Examples of these problems are the ocean and atmosphere interaction, the global ocean circulation, and the global change (GC) [1]. The measures of the decline in primary productivity in the Pacific Ocean by sensors operating in the visible [2] and the rise of the sea surface using altimeters [3]–[5] are two of the most prominent examples of the influence of GC in the oceans.

Satellites have contributed to the study of these problems by providing an enormous quantity of information, mainly in the form of images in different bands of the electromagnetic spectrum. For a typical research and educational application, terabytes of geospatial images and other data are required [6]. As an example, the Envisat satellite acquired about 1 TB of data per day.

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J. A. Piedra-Fernández, G. Ortega, and M. Cantón-Garbín are with the Department of Informatics, University of Almería, 04120 Almería, Spain.

J. Z. Wang is with the College of Information Sciences and Technology, The Pennsylvania State University, University Park, PA 16802, USA.

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In the case of the oceans, the major part of the ocean circulation is the mesoscale circulation (scales of 50–500 km and 10–100 days), whose energy is at least one order of magnitude higher than the general circulation [7], [8]. The components of the mesoscale circulation are cyclonic and anticyclonic gyres, fronts, jets, and meanders. Upwellings are another important mesoscale structure [9]–[12].

Sometimes and independently of the volume of the data, there is no precise definition of the mesoscale structures that we could identify in the satellite images. Moreover, the mesoscale ocean structures have a high variability in shape and a fast change in location.

Pattern recognition and automatic image understanding in remote sensing are important fields to manage the large volume of data acquired from the space during the last 40 years. One example of this importance is the effort at ISFEREA (Geospatial Information Analysis for Security and Stability, Joint Research Centre, Ispra, EU) that has developed an image information query system (I2Q) designed to process massive and heterogeneous remotely sensed image data [13].

The large volume of environmental data received from satellites during the past decades and the needs for studies of the GC and predictions about the evolution in the mesoscale ocean dynamics motivated us to develop a content-based image retrieval (CBIR) [14] system to automatically interpret the sea surface temperature (SST) maps obtained from the Advanced Very High Resolution Radiometer (AVHRR) sensors from the National Oceanic and Atmospheric Administration (NOAA). The grayscale SST image can be split into bands of 1 °C for each of the ten gray levels (from 0 to 255 gray levels). The lowest value of 1 (dark gray color) corresponds to temperature around 10 °C, and the highest value of 254 (light gray color) corresponds to temperature around 30 °C. The CBIR system includes several types of soft computing technologies [15], such as neural networks [16], [17] and fuzzy logic [18], [19]. An advantage of this approach is that the system can be more comprehensible to human users because fuzzy databases (DBs) manage a terminology close to natural languages. In this kind of systems, classifiers play an important role [20]–[25].

A. Problem Description

There are several mesoscale structures that we are interested in locating. These oceanic structures are *upwellings, wakes, cold-core eddies*, and *warm-core eddies* (see Fig. 1). They are defined as follows:

Upwellings are cool and nutrient-rich waters that emerge to the surface of the oceans as a result of winds (trade winds in the

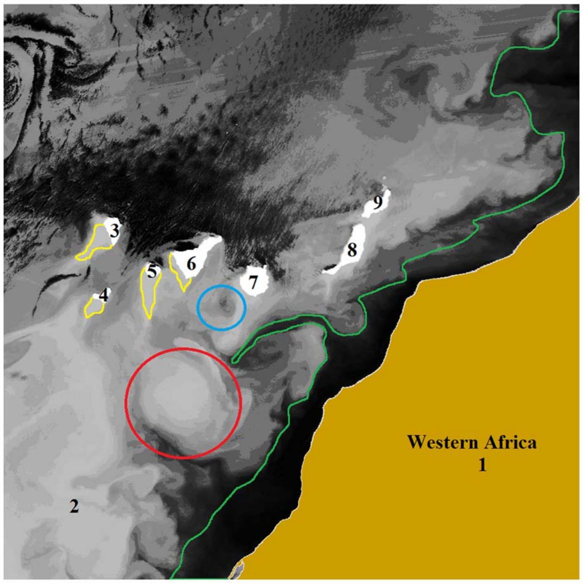

Fig. 1. AVHRR scene (08/10/1993) showing (1) western Africa, (2) the sea and the Canary Islands [(3) La Palma, (4) El Hierro, (5) La Gomera, (6) Tenerife, (7) Gran Canaria, (8) Fuerteventura, and (9) Lanzarote]. The oceanic structures are enhanced: (green color) *upwellings*, (red color) *warm-core eddies*, (blue color) *cold-core eddies*, and (yellow color) *wakes* for La Palma, El Hierro, La Gomera, and Tenerife.

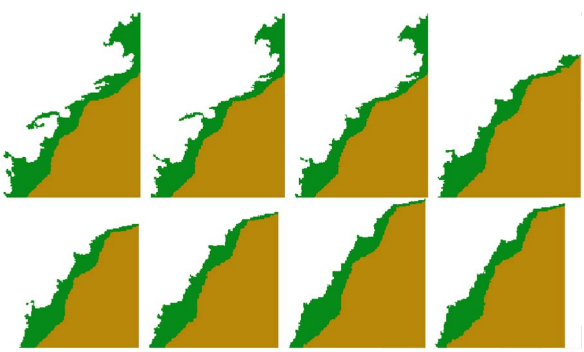

Fig. 2. Examples of regions that can be considered as (green color) *upwellings* next to (brown color) the African continent.

Canary Islands) blowing from the NE parallel to the coast, combined with the effect of the Coriolis force over the surface layers of the ocean. These waters rich in nutrients such as nitrates and phosphates fertilize the phytoplankton, and in this way, all the trophic chains develop from phytoplankton to pelagic species [11], [26]. Upwelling structures are very important and scarce. They are very important from an economic point of view because the most fertile and richest feeding ground for fishing are located next to them. In Fig. 2, different regions that can be considered upwellings are shown in green color. Another example is observed in green color in Fig. 1.

Eddies are rotating water masses that emerge or sink into the ocean with abrupt changes in temperature and salinity. When the core of the eddy has a lower temperature than the surrounding zones, it is named cold-core eddy and, in the opposite case, hot eddy. In cold-core eddies, the vertical movement is ascending; cold water, rich in nutrients, rises to the surface. However, warm-core eddies accumulate and sink warm water, carrying organic matter downward toward the ocean depths [11].

Island warm wakes appear as a result of leeward calm areas produced by the existence of islands.

For the development of our classification and retrieval system, we have considered an area whose main characteristic is the presence of all the mesoscale oceanic structures previously described. This area is located among the NW coast of Africa, the Canary Archipelago, and the Iberian Peninsula in the Atlantic Ocean. Our area of interest is enclosed in an area that extends from 19° N to 45° N in latitude and from 2° W to 21° W in longitude. The work can be readily applied to other places in the ocean. Our system is evaluated using satellite images acquired by AVHRR satellite sensors of NOAA satellite series during the years from 1988 to 1993. However, the methodology that we have developed in this paper can be used with any other set of images corresponding to other sensors such as Sea-viewing Wide Field-of-view Sensor (SeaWiFS), Moderate Resolution Imaging Spectroradiometer (MODIS), Advanced Along-Track Scanning Radiometer (AATSR), or MEdium Resolution Imaging Spectrometer (MERIS), among others.

B. State of the Art

A CBIR system [27] is any technology that helps to organize digital picture archives by their visual content. They are useful for managing very large unannotated image collections. Several relevant studies on the classification and retrieval of satellite images are found in [28] and [29]. A data mining system that combines an auto-annotation component with image classification was developed in [30]. Image classification and searching algorithms to find similarity based on shape features from satellite imagery data were combined in [31].

In the literature, many researchers and institutions have published on CBIR. Datta *et al.* [14] from The Pennsylvania State University (Penn State) have studied the challenges involved in the adaptation of existing image retrieval techniques to build systems that can be useful in real-world applications. Moreover, Datta *et al.* analyzed and quantified the current progress and future uses and developments of image retrieval. The group at Penn State [32] has developed some well-known CBIR systems, such as a machine-assisted image tagging and searching service that handles millions of images in real time named Automatic Linguistic Indexing of Pictures - Real Time (ALIPR) [33]. Nevertheless, ALIPR has been developed to work only with visible spectrum images, but currently, satellite sensors are capable of acquiring multispectral images. To overcome this limitation, our CBIR incorporates multispectral images from different satellite sensors.

Focusing our attention on remote sensing CBIR, several systems have been proposed [34]–[39] for retrieving satellite images. In [39], an approach for selecting and blending bio-optical algorithms using an ocean color satellite image is described. Our CBIR system is based on a web-based image DB that classifies and retrieves mesoscale oceanic structures in real time.

Our CBIR system is novel because it combines fuzzy logic and geospatial information for the retrieval and classification of images. The main advantage of our system is that it includes fuzzy knowledge in the semantic image retrieval. This fuzzy

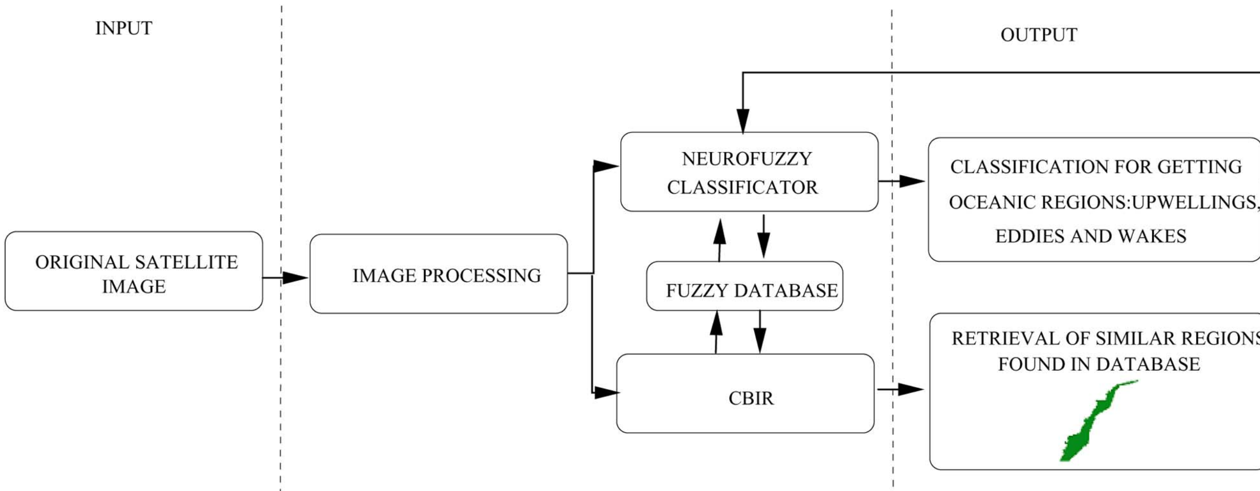

Fig. 3. Structure of the system for the classification and retrieval of mesoscale oceanic structures where the input, the modules for the retrieval and the classification of mesoscale structures (i.e., upwellings), and the outputs are observed.

knowledge reduces the semantic gap between extracted visual features and semantic concepts. Another innovative aspect of this system is that it provides a tool for working with multispectral images from different satellite sensors. The system represents a new approach for retrieval and classification of mesoscale oceanic structures combining fuzzy logic with multispectral images.

C. System Design

The structure of the system for the classification and retrieval of mesoscale oceanic structures is shown in Fig. 3.

- Input: Original satellite image.
- Output: There are two possible outputs in the CBIR system: 1) the classification of regions of interest that appear in the image; and 2) the retrieval from the DB of similar images with one or more structures similar to those found in the input image.
- Image processing: A set of steps to improve the quality of the original image. Image processing is described in detail in Section II.
- CBIR system connected to a fuzzy DB. The CBIR system allows retrieving images with similar mesoscale oceanic structures.
- Neurofuzzy classifier to classify the regions of the fuzzy DB into one of the outputs of the system (i.e., upwellings, eddies, or wakes).
- Fuzzy DB: The CBIR and the neurofuzzy classifier are connected to a fuzzy DB, which allows efficient managing and searching of satellite images due to the fact they are organized without redundancies. Fuzzy structured query language (FSQL) [40] is the query language to execute fuzzy queries. FSQL incorporates some innovations over structured query language (SQL) to allow the management of fuzzy information. In order to use FSQL over a DB management system (DBMS) such as Oracle, the FSQL server for a fuzzy relational DB (FRDB) is used [41]. The main feature of the FSQL server is the inclusion of fuzzy attributes to store vague information in the tables of the DB.

The obtained system is supported by the client-server paradigm, which is accessible by web clients. The server maintains the image DBs and processes the CBIR queries. The clients only need a web browser to access the server. There are five main advantages of this paradigm.

- The system is constantly updating the knowledge base.
- Knowledge shared between all users: Contributions of every expert are shared by all users.
- Centralized information: It allows to avoid both the redundancy and the incoherences in the information.
- Efficiency and backup.
- High-speed processing: The data processing algorithms are performed by the server so that the client does not need to be of high computing power.

D. Outline of the Paper

Section II describes the methodology of the solution describing the main steps of the CBIR system, i.e., image processing, feature extraction, neurofuzzy classification, and fuzzy retrieval. In Section III, the processes of classifying and retrieving of regions of interest are discussed. Moreover, the obtained results for the classification and retrieval processes are analyzed. Additionally, a comparison with the results obtained by other classifiers is included. Finally, Section IV summarizes the main conclusions and suggests further improvements.

II. Methodology of the Solution

The fuzzy CBIR system is composed by (see Fig. 4) these four steps.

- *Satellite image processing*. The most important task is the iterative segmentation using a graphic expert system.
- *Feature extraction*. Morphological and contextual descriptors are calculated, and the fuzzy value associated to each one is assigned.
- *NEuroFuzzy CLASSification*. NEFCLASS has been developed for the classification of oceanic structures.

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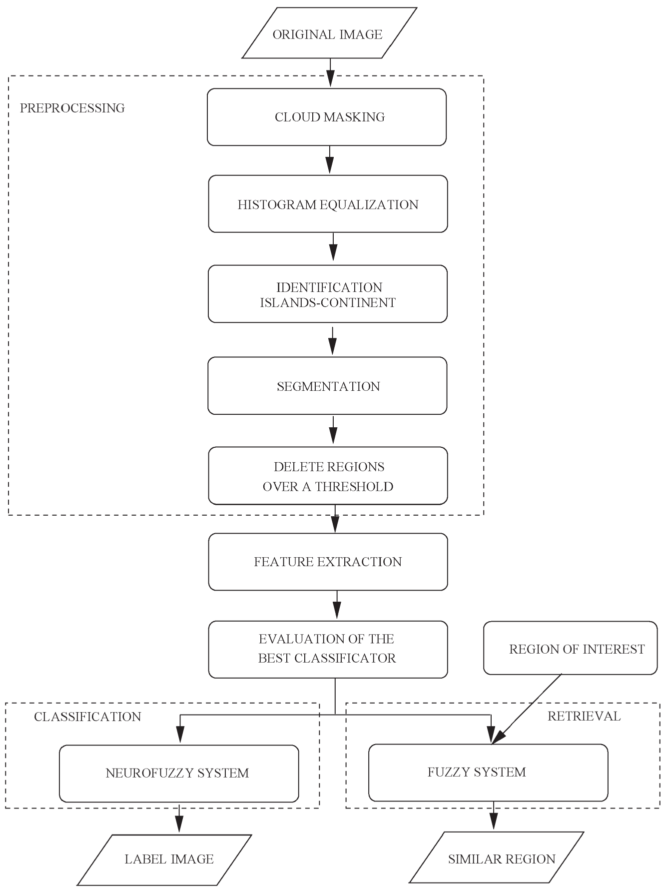

Fig. 4. Components of the CBIR system where the four main sections (i.e., image processing, feature extraction, neurofuzzy classification, and retrieval by means of fuzzy queries) and their subsections can be observed.

- *Fuzzy queries*. The human expert can search oceanic structures using a language with a structure close to natural language.

A. Image Processing

The goal of satellite image processing is to improve the quality of images for the next steps. These are the image processing techniques over the original images.

1) Automatic cloud masking process [42] detects cloud pixels that are opaque to the ocean radiance data measured in the AVHRR infrared and creates a mask of zeros for these areas (see Fig. 5). In the algorithm, every unusually cold region and areas with a high value of the standard deviation around every pixel of the region are considered as clouds and rejected by our system.
2) Histogram equalization for maximizing the contrast of the original image without losing structural information. This equalized image makes the task of manual classification by experts easier. Fig. 6 shows the original and the equalized images. As can be observed, without the histogram equalization, it would be more difficult for the human experts to locate regions of interest.
3) Identification of islands and continent by means of an algorithm that defines the continent like the portion of land cut by the right edge of the image. The islands are identified because they are surrounded by water.
4) Iterative segmentation through an expert graphic system [43], in order to obtain the regions in the image that are going to be classified. The graphic system divides the image in parts (regions) that can be associated to an object of the reality and could be oceanic structures. Fig. 7 shows an example of one image after an iterative segmentation, where every different color represents a region of interest.
5) Deletion of regions with area larger or smaller than several pre-established thresholds (called noninterest regions). In this way, regions with an area smaller than the

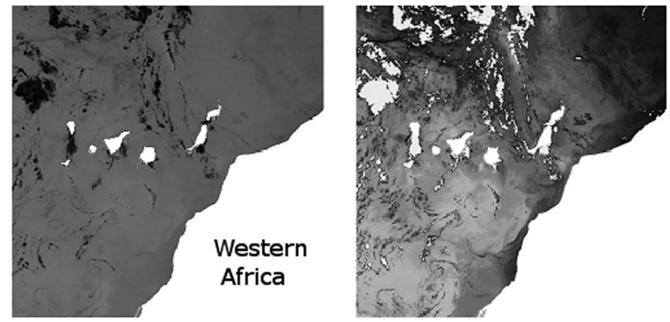

Fig. 5. AVHRR scene (08/04/1988). Comparison between (left) the original image and (right) the same image after the automatic cloud masking process. Note that clouds after the cloud masking process are represented in white color. They are not considered for the classification process.

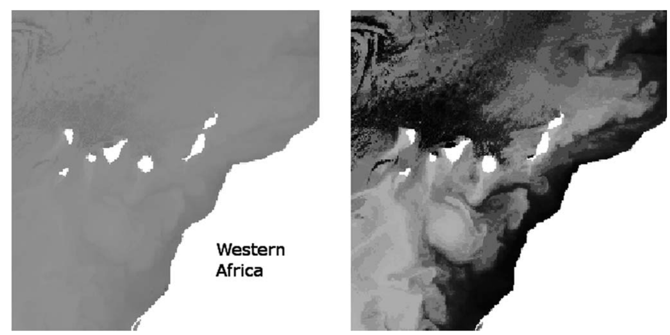

Fig. 6. AVHRR scene (08/10/1993). Comparison between the (left) original and (right) equalized images. The purpose of the equalized image is to maximize the contrast for showing more visual details to the human user in the final image.

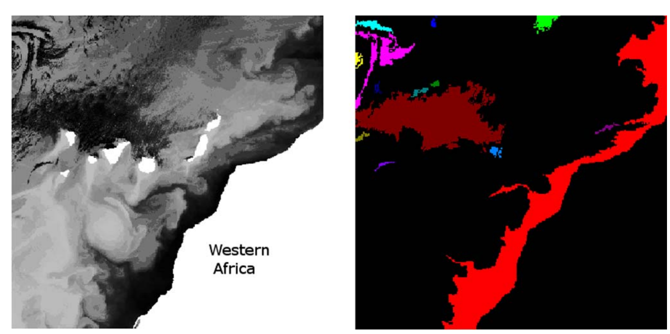

Fig. 7. AVHRR scene (08/10/1993). Comparison between the (left) original and (right) segmented images. Note that, in the segmented image, the black region is composed by noninterest regions and the regions of interest are represented by color regions.

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smallest island (El Hierro) or regions with an area bigger than the 20% of the image (the size of the highest oceanic structure) are not considered in the CBIR system.

B. Feature Extraction

After the region segmentation step, a feature extraction process is applied. This process is based on the representation of a region of the image by means of a vector whose components are numeric and contextual descriptors. Let us emphasize the importance of this process in CBIR since after the feature extraction, we will work only with the vectors that represent the morphology of every region rather than its pixel values.

Let us focus our attention on the morphological descriptors. The main morphological descriptors used are perimeter; area; volume; volume^2; density; gray levels: minimum, maximum, average, and standard deviation; gray level barycenter; equivalent diameter; bounding ellipse: major and minor axes, orientation, eccentricity, degree of circumscription, and centroid; barycenter; bounding box and area; Hu's invariant moments [44]; Maitra's invariant moments [45]; Zernike's invariant moments [46]; Canton's moments: first and second order; and inertia moment eccentricity [47]. Some of these morphological descriptors (e.g., invariant moments, density, quotient of major, and minor bounding ellipse axis) are invariants under affine transformations. As a result, the regions can be recognized despite rotations, translations, or scale changes over the image.

In addition, two contextual descriptors have been implemented according to the oceanographers' knowledge. These two contextual descriptors use the region-inferred knowledge beyond pixel information [48].

- *Temperature difference (TempDiff)*: This descriptor calculates the temperature difference between the center and the edge of a structure. It is useful to discriminate between *warm-* or *cold-core eddies*. The first one has a warm nucleus, and the second one has the interior zone of lower temperature than the exterior. It is enough to calculate the average temperature in every zone and then to determine the difference.
- *Minimum distance to islands* and *continent (DistToLand)*: This is the minimum distance between the structure and the continent or the islands (see Fig. 8).

After the feature extraction, the image is stored in the DB in terms of feature vectors. These feature vectors (hereinafter, descriptors) will allow the classification and retrieval of relevant regions in satellite images. Note that the selection of the suitable descriptors to classify and retrieve is highly relevant.

C. Neurofuzzy System for Classification

Neurofuzzy systems refer to combinations of artificial neural networks and fuzzy logic for solving neural networks and fuzzy system problems. Fuzzy logic is basically a multivalued logic that allows handling the concept of partial truth rather than the absolute values and categories in Boolean logic [49]. The neurofuzzy system considered for our system is the NEFCLASS [50] because the data analysis by neurofuzzy models is legible and efficient.

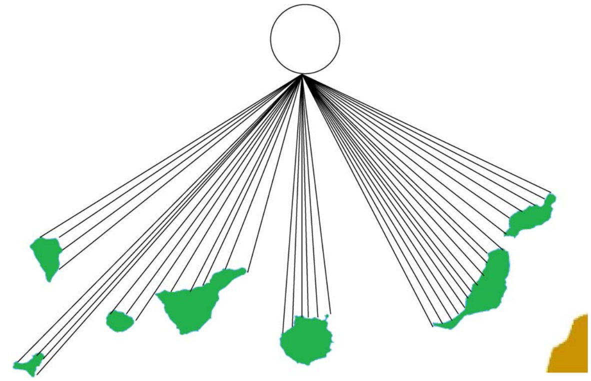

Fig. 8. Illustration of the minimum distance to islands and continent descriptor (DistToLand). The black circle identifies the oceanic structure, the green regions are the islands, the brown region is the African continent, and the black lines represent the possible minimal distances between the oceanic structure and the islands.

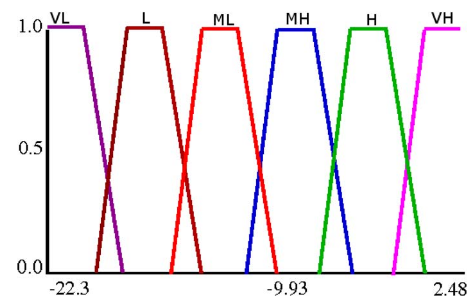

Fig. 9. Temperature difference descriptor with six trapezoidal MFs. Six linguistic labels, i.e., very low (VL), low (L), medium-low (ML), medium-high (MH), high (H), and very high (VH), have been used.

Once the descriptors are inserted into the DB, the creation of a classifier is possible. This classifier will be used for the process of classification of mesoscale oceanic structures of satellite images. The neurofuzzy classifier is built by means of three-slice neural networks: 1) descriptors; 2) fuzzy rules; and 3) output (e.g., *wake* and *upwelling*).

To generate the fuzzy rules, the membership function (MF) type and the maximum number of fuzzy rules have to be established. In our particular case, the MF type considered is a trapezoidal function because this function permits to represent the human expert knowledge of any concept and produce better result than other functions [40]. For our CBIR system, all the descriptors described in Section II-B are set up by j MFs. For instance, we can consider that the temperature difference descriptor has four MFs and, hence, four linguistic labels (low, medium-low, medium-high, and high) or six MFs (see Fig. 9).

Experimental results show that when six MFs are considered, a more efficient classification is obtained, but the complexity of rules has increased and the legibility of the fuzzy system has decreased.

On the other hand, an excessive number of rules turns the system into a black box impossible to understand by a human being, whereas a too limited number is insufficient for an optimum classification. As a result, it is necessary to find a compromise between accuracy rate and number of rules.

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NEFCLASS allows to start using rules defined by the user or the DB can be built with a training period. Let us remark that every class must have a fuzzy rule at least.

A fuzzy rule $R1$ for the resolution of classification problems has the general form as follows:

$R1$: If x_1 is low and ... and x_n is $medium - low$, then y belongs to c class.

Let us remark in $R1$ that $x_1 \ldots x_n$ are the different descriptors, $low \ldots medium - low$ are the linguistic labels, y is the region to classify, and c is the output oceanic structure. An example of fuzzy rule in our system could be: IF *Distance to Islands* is low AND *temperature* is high THEN is a wake.

One characteristic of our NEFCLASS system is that it allows fuzzy sets training cyclically until a suitable stopping criterion is reached.

Moreover, corrections over the MF can be applied for the system in order to obtain a better result with a particular rule. This correction cannot break any user restrictions, such as a function cannot exceed another one, the degrees of membership for a given value of the variable always add to one, or fuzzy sets have to be symmetric.

To obtain the best classifier for the classification of mesoscale oceanic structures, a comparative study using different classifiers has been carried out. The classifier that produced the fewest misclassifications was composed by 4 descriptors (*DistToLand, degree of circumscription ellipse, invHu1* or Hu invariant moment 1, and *TempDiff*), trapezoidal MFs, and 11 rules. Some rules of the classifier are shown as follows.

- IF *DistToLand* is low AND *degree of circumscription ellipse* is medium-low AND *invHu1* is low AND *TempDiff* is high, THEN is a *wake*.
- IF *DistToLand* is medium-low AND *degree of circumscription ellipse* is low AND *invHu1* is high AND *TempDiff* is medium-high, THEN is an *upwelling*.
- IF *DistToLand* is high AND *degree of circumscription ellipse* is high AND *invHu1* is low AND *TempDiff* is high, THEN is a *warm-core eddy*.

D. Fuzzy Logic for Image Retrieval

The retrieval of oceanic structures consists of locating similar regions in the image DB to the specified query. In our case, the retrieval is carried out by means of the execution of fuzzy queries on the system DB.

For the retrieval of oceanic structures, the creation of a classifier composed of descriptors is required. When the classifier is created, fuzzy information is stored into the fuzzy DB (see Section II-E). For our particular problem, the set of suitable descriptors for solving the problem has been proposed by oceanography experts.

Automatic image retrieval using fuzzy logic can be described in the following steps (see Fig. 10).

- The user has to select a specific oceanic region for retrieving. In Fig. 10, the region marked in green is an *upwelling* (the region with green border). Note that from the fuzzy data information of a region, a fuzzy query can be executed to retrieve similar regions to one given, which is the concept of CBIR. Moreover, simple modifications in the CBIR would allow us to execute queries by concept and content.
- The system searches among all existing regions in the fuzzy DB and selects with a degree of similarity (equal or higher) all similar regions. Note that retrieved regions by the system will depend on both the selected descriptors and the configuration parameters of the MFs related to each descriptor. For our particular problem, the set of suitable descriptors for solving the problem has been proposed by oceanography experts.

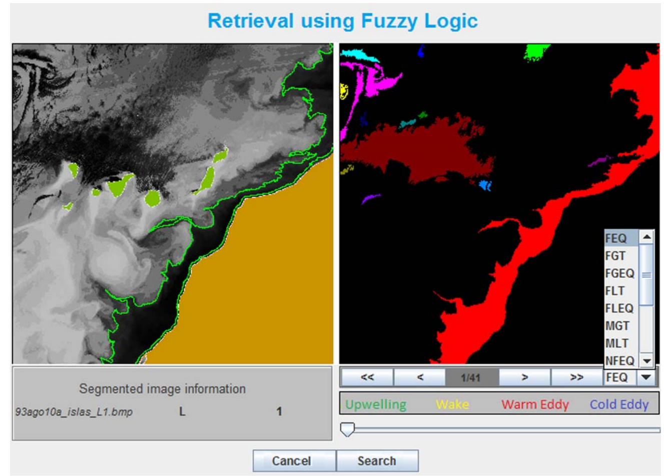

Fig. 10. AVHRR scene (08/10/1993). Automatic image retrieval example. (Left) Original image in which the region marked on the segmented image is represented (with green border). (Right) Segmented image with regions of interest in which the region to retrieve will be selected.

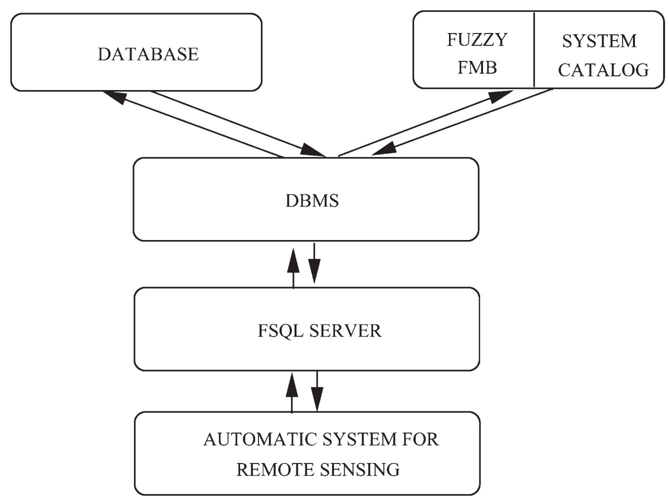

Fig. 11. FRDB architecture of image retrieval.

E. Fuzzy DB

The system for fuzzy retrieval and management of fuzzy information is made up by these five parts (see Fig. 11).

- DB. The DB stores in a relational format all the descriptors associated with each image. The main characteristic of the DB is that it has been extended to manage vague information, and it is possible to store the fuzzy attribute values.

- Fuzzy Meta-knowledge base (FMB). The FMB consists of a set of tables created in the Oracle DB in order to store fuzzy information about the values included in the DB. When the descriptors are stored in the DB, the columns of the FMB are modified for storing all fuzzy attributes related to the descriptor [name (e.g., temperature difference), MFs, and linguistic labels].
- System catalog. The system catalog is the data dictionary of the DBMS. It stores tables that contain information about the definitions of the DB objects (e.g., tables, views, indexes, and packages).
- DBMSs. The DBMS considered has been Oracle because of its power, flexibility, and ability to program packages. The requests to the FRDB could involve fuzzy conditions. In this case, they are processed by the FSQL server.
- FSQL server. It is necessary because Oracle only allows the use of SQL instead of FSLQ sentences. The objective of this server is to translate an FSQL query into a standard SQL sentence. For this translation, the server uses the fuzzy information stored in the FMB.

III. Analysis and Results

This section evaluated test examples for both the neurofuzzy classification and the fuzzy retrieval. For these evaluations, 298 image regions have been considered (i.e., 35 *upwellings*, 100 *wakes*, 10 *cold-core eddies*, 10 *warm-core eddies*, and 143 *unknown regions*). Note that runtimes for the image retrieval of regions of interest are less than 0.001 s.

A. Results of the Neurofuzzy Classifier

In this section, some results of the process of neurofuzzy classification using different test examples are shown. Several classifier configurations have been considered to check the quality of the neurofuzzy classifier for oceanic structure classifications. Here, the knowledge of oceanographers has been required for identifying the most relevant descriptors in the creation of the classifiers. As a result, the best classifier is composed by two contextual descriptors [minimum distance to islands and continent *(DistToLand)* and temperature difference *(TempDiff)*] and two morphological descriptors [degree of circumscription ellipse *(degree of circumscription ellipse)* and the first Hu invariant moment *(invHu1)*]. On the one hand, the knowledge of oceanographers has been used to select the three descriptors of the classifier: 1) TempDiff gives us information about the temperature; 2) DistToLand gives us information about the structure position; and 3) the orientation of the circumscribed ellipse gives us information about the orientation of the region. On the other hand, Hu's invariant moment 1 gives us information about the shape and orientation of the structure. In our automatic feature selection system [48], Hu's invariant moments got a high ranking score in the classification process improving the accuracy rate. In fact, the best ranking score was obtained by invHu1. NEFCLASS was tested with these four descriptors using several setting of rules and MF number.

The main characteristics of this classifier are: 1) the use of only four descriptors decreases the complexity of the generated fuzzy rules and improves its legibility; and 2) the system obtains real-time results with a high accuracy rate.

TABLE I
RESULTS OF NEFCLASS CLASSIFIER USING THE DESCRIPTORS (DistToLand, Degree of Circumscription Ellipse, invHu1, AND TempDiff), A MAXIMUM OF 11 RULES, AND WITH DIFFERENT NUMBERS OF MFs (4, 6, 8, AND 10)

Classifier	(%)Accuracy Rate	(%)Classified false positives
CL4MF	**100**	**5.15**
CL6MF	76.25	3.03
CL8MF	76.34	3.03
CL10MF	20.15	1.10

TABLE II
RESULTS OF NEFCLASS CLASSIFIER USING THE DESCRIPTORS (DistToLand, Degree of Circumscription Ellipse, invHu1, AND TempDiff), DIFFERENT RULE NUMBERS, AND NUMBER OF MFs

Classifier	MFs	Rules	(%)Accuracy Rate
NEFCLASS	**4**	**11**	**85.34**
NEFCLASS	4	20	80.18
NEFCLASS	6	11	73.04
NEFCLASS	6	15	75.23
NEFCLASS	8	11	70.67
NEFCLASS	8	29	78.45
NEFCLASS	10	11	60.23
NEFCLASS	10	32	78.36

Table I shows the results obtained for the classifier composed by the four descriptors (*DistToLand, degree of circumscription ellipse, invHu1*, and *TempDiff*) and a maximum of 11 rules. Note that classifiers are called as follows: classifier (CL) and the number of MFs for descriptor (MF). In particular, the classifiers considered are CL4MF, CL6MF, CL8MF, and CL10MF.

In Table I, two different parameters can be identified: 1) the classification of real regions; and 2) the false positives. The first column [(%) Accuracy Rate] describes the percentage of regions that have been detected and, therefore, classified. The second column [(%) Classified false positives] identifies the classified regions that are not valid. The results in Table I have been obtained fixing the rule number to 11 and modifying the number of MFs (4, 6, 8, and 10). When the number of MFs increases, the number of generated rules naturally increases. Thus, the accuracy rate in terms of the classification of real regions is lower with 10 MFs and 11 rules. In Table II, this conclusion is observed on the results, where for each number of MFs, two cases are shown, i.e., the local maximum accuracy rate and the accuracy rate using 11 rules (because it is the best accuracy rate). The local maximum accuracy rate means that the relative maximum of accuracy rate depends on the rule number for a fixed number of MFs and descriptors in the test process. In the first row, we obtained the maximum accuracy rate using 11 rules. Although, in the second row, the accuracy rate decreases when the rule numbers increase to 20, but in the rest of the cases, when the MFs increase, the rule's number is adapted, growing until the local maximum accuracy rate. In general, the accuracy rate depends on the number of MFs, on the rule's number, and on the number of descriptors. The local maximum accuracy rate can be usually detected for a fixed number of descriptors and MFs using different rule numbers. In the last case, it is observed that the local maximum accuracy rate is getting for 32 rules and 10 MFs, although in the first case, it is getting for 11 rules and 4 MFs.

TABLE III
RESULTS OF ACCURACY RATE USING DIFFERENT CLASSIFIERS, NUMBER OF MFs, RULES, AND NUMBER OF DESCRIPTORS. THE TWO BEST VALUES IN TERMS OF ACCURACY ARE TYPED IN BOLD FOR EVERY CLASSIFIER

Classifier	Descriptors	MFs	Rules	(%) Accuracy
ANFIS	4	4	233	60.40
ANFIS	11	4	290	55.26
ANFIS	75	4	338	50.45
ANFIS	4	9	392	76.84
ANFIS	11	9	393	79.26
ANFIS	75	9	438	72.45
ANFIS	4	15	407	**83.63**
ANFIS	11	15	393	**85.03**
ANFIS	75	15	438	73.45
NEFPROX	4	4	220	65.04
NEFPROX	11	4	290	58.60
NEFPROX	75	4	302	55.52
NEFPROX	4	9	392	75.84
NEFPROX	11	9	393	76.65
NEFPROX	75	9	433	61.27
NEFPROX	4	15	407	**88.02**
NEFPROX	11	15	393	87.52
NEFPROX	75	15	435	**89.65**
NEFCLASS	4	4	11	85.34
NEFCLASS	11	4	11	70.02
NEFCLASS	75	4	11	65.84
NEFCLASS	4	9	32	78.34
NEFCLASS	11	9	45	77.66
NEFCLASS	75	9	57	69.32
NEFCLASS	4	15	39	81.02
NEFCLASS	11	15	49	70.05
NEFCLASS	75	15	73	69.08
NEFCLASS	4	50	87	85.77
NEFCLASS	11	50	111	77.87
NEFCLASS	75	50	182	76.47
NEFCLASS	4	100	316	**94.19**
NEFCLASS	11	100	327	93.39
NEFCLASS	75	100	489	**98.30**

TABLE IV
RESULTS OF ACCURACY RATE USING DIFFERENT CLASSIFIERS AND NUMBER OF DESCRIPTORS

Classifier	(%)Accuracy 75 descriptors	(%)Accuracy 11 descriptors	(%)Accuracy 4 descriptors
NEFCLASS	**98.30**	93.39	**94.19**
NB	89.18	94.59	83.78
C4.5	94.59	94.59	91.89
MLP	97.29	**100**	89.18
FLR	91.89	**100**	89.18

Furthermore, a comparison of NEFCLASS with other neuro-fuzzy classifiers has been carried out in Table III. The classifiers were tested using all descriptors (in our case, 75 descriptors), an automatic feature selection (only 11 descriptors), and an experimental feature selection based on the results obtained by neurofuzzy classifiers (see Section III). The automatic feature selection is a technique that combines filter methods and Bayesian classifier as a feature selector [48]. Adaptive-Network-based Fuzzy Inference System (ANFIS) [51] and NEFPROX [52] need a higher rule's number and give worse accuracy rate than NEFCLASS. In general, for the three classifiers, the accuracy rate using 4 descriptors is close to the values using 75 descriptors. In addition, in ANFIS and NEFPROX, the rule's number is three or four times higher than with NEFCLASS.

Table IV shows a comparative analysis among different classifiers such as Naıuml;ve Bayesian network (NB), decision tree using C4.5 model, multilayer perceptron neural network (MLP) [53], and fuzzy lattice reasoning (FLR) [54]. The best classifications were obtained using 11 descriptors and the automatic features selection by MLP and FLR (100% of accuracy for both). Note that, in a fuzzy system, the accuracy rate depends on the number of MFs and on the number of rules considered. We should emphasize that NEFCLASS and FLR are easier to understand by humans because these classifiers work with fuzzy rules close to the real-world meanings. Of course, the accuracy rate of MLP using 11 descriptors is the highest, but the knowledge representation is more difficult to understand by the human expert. NB uses a probabilistic knowledge and not fuzzy knowledge; although the model structure is simple, it is hard to determine the relationship between descriptors and to extract rules understandable by the human being. Although C4.5 is easily understandable, in this case, the main problem was the size of the tree, more than 150 levels in the worst case and 40 in the best case. It is difficult to be understood by the human being. The best classification according to lowest descriptor number, highest accuracy rate, and easily of understanding was by NEFCLASS. Note that, in Table IV, NEFCLASS with four descriptors obtained better accuracy rate than MLP and FLR with four descriptors. When this classifier uses four descriptors, fuzzy rules are easily understandable and the efficiency is between 2.5 and 9, better than other classifiers. The NEFCLASS's computational cost was higher during the training step around 2 s, although the highest time was around 30 s by MLP. During the testing step, the computational cost was less than 1 s, although the fastest was by C4.5.

TABLE V
RETRIEVAL OF OCEANIC STRUCTURES BASED ON CLF4MF

Structure	(%)Accuracy Rate	(%) Retrieved false positives
Upwellings	100	20.36
Cold-core eddy	80.25	30.20
Warm-core eddy	100	26.04
Wakes	88.35	8.12

B. Results of the Fuzzy Retrieval System

In this section, some results of the process of fuzzy retrieval using different test cases are shown. In this paper, a variety of queries using the combination of several descriptors and a set of 298 regions stored in the DB have been performed. Table V shows the best results obtained with the CLF4MF classifier for each oceanic structure.

In Table V, the "percentage of accuracy rate" means that if there are 100 oceanic structures of type *cold-core eddies*, our system will correctly retrieve 80.25 of them (and also some false positives). The column "false positives in retrieved regions" shows the percentage of false positives between all the positives. Analyzing the results in Table V, we are going to focus our attention in two parameters: 1) the retrieval of real regions; and 2) the valid/false positives. The first parameter depends on the nature of the region. The retrieval of real mesoscale oceanic regions depends on the kind of the region. Our system detects all upwellings and warm-core eddies correctly. Nevertheless, the system does not correctly distinguish all cold-core eddies and wakes structures. This problem could be solved by creating a new classifier (with more descriptors) to retrieve these types of mesoscale oceanic structures with higher accuracy. The number of false positives is directly related to the number of oceanic structures of each type included in the DB. That is, the more oceanic structures in the DB, the less number of false positives (i.e., upwellings and wakes have the highest number of regions in the DB and the less number of false positives). To overcome the problem of a high number of false positives, the solution would be the gradual inclusion of more oceanic structures into the DB.

IV. Conclusion and Future Work

This paper has presented a CBIR system that allows the classification and retrieval of mesoscale oceanic structures from satellite images. The runtime executions for the classification and image retrieval of regions of interest are less than 0.001 s. The location of these oceanic structures is very relevant for the study of marine circulation, atmosphere–ocean exchange, and GC, and it also has an economic importance. Soft computing technologies such as neurofuzzy and fuzzy logic have been considered for solving the problem. On the one hand, classification using neurofuzzy systems offers several advantages with regard to systems based on Bayesian or neural networks. The neurofuzzy system has higher accuracy rate, and the knowledge generated is reusable. On the other hand, fuzzy systems are open systems with legible rules for a human expert and can be modified. The FSQL technology allows us to look for relevant regions quickly from a huge data set of images. The system executes a fuzzy query to retrieve reasonable coincidences (similar descriptors). The fact of using fuzzy logic allows us to find regions similar to one selected by the user in the image data set. The user selects the region and also the fuzzy possibility comparator to execute the fuzzy queries. The use of FRDBs allows us to manage information in an organized and efficient way and to make the fuzzy retrieval of interest regions easier.

This system can be easily extended for working with other regions of the oceans in order to locate other mesoscale oceanic structures or can be adapted for working with other kind of images (Cl-a in SeaWiFS, MODIS, MERIS, or Coastal Zone Color Scanner; SST from MODIS and AVHRR; synthetic aperture radar; and also altimeters (ALT) ocean structures). For this purpose, the evaluation and exploration of new descriptors will be required, particularly contextual descriptors based on the particular problem to study. Currently, we are improving our CBIR system using ontologies to combine data from multiple heterogeneous sources. In the meantime, we are going to extend these studies to the North Atlantic and North Pacific oceans using MODIS, SeaWIFS, and meteorological data. The goal of this work will be to forecast natural disasters such as cyclones and tropical storms by studying the SST, chlorophyll concentration, and meteorological data.

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Jose A. Piedra-Fernández was born in Spain in 1978. He received the Bachelor's degree in computer science and the M.S. and Ph.D. degrees from the University of Almería, Almería, Spain, in 2001, 2003, and 2005, respectively.

He is currently an Assistant Professor with the University of Almería. He visited the College of Information Sciences and Technology, The Pennsylvania State University, University Park, PA, USA, in 2008–2009. His main research interests include image processing, pattern recognition, and image retrieval. He has designed a hybrid system applied to remote sensing problems.

Gloria Ortega received the M.Sc. degree in computer science in 2010 from the University of Almería, Almería, Spain, where she is currently working toward the Ph.D. degree.

Her current research work is focused on high-performance computing. She is mainly involved in the parallelization of algebraic routines and the development of a physical model based on optical diffraction tomography. Other major research interests include image processing and soft computing.

James Z. Wang received the Bachelor's degree (*summa cum laude*) in mathematics and computer science from the University of Minnesota-Twin Cities, Minneapolis, MN, USA, and the M.S. degree in mathematics, the M.S. degree in computer science, and the Ph.D. degree in medical information sciences from Stanford University, Stanford, CA, USA.

Since 2000, he has been a Faculty Member with The Pennsylvania State University, University Park, PA, USA, where he is currently a Professor with the College of Information Sciences and Technology. He was a Visiting Professor with The Robotics Institute, Carnegie Mellon University, Pittsburgh, PA, in 2007–2008 and a Program Manager with the National Science Foundation in 2011–2012. His main research interests are automatic image tagging, image retrieval, computational aesthetics, and computerized analysis of paintings.

Prof. Wang was a recipient of a U.S. National Science Foundation CAREER Award and the endowed PNC Technologies Career Development Professorship.

Manuel Cantón-Garbín was born in Adra (formerly Abdera), Almería, Spain, in 1955. He received the Bachelor's degree in physics (electronics) from the University of Granada, Granada, Spain, in 1979 and the M.S. and Ph.D. degrees from the University of La Laguna, San Cristóbal de La Laguna, Spain, in 1980 and 1982, respectively.

In 1984, he moved to the University of Las Palmas de Gran Canaria (ULPGC), Las Palmas de Gran Canaria, Spain, and in 1986, he led the first group in Spain working on satellite oceanography. In 1986, he became a Lecturer, and in 1991, a Full Professor in applied physics with ULPGC. In 1994, he moved to the University of Almería, Almería, where he is currently a Full Professor in computing and artificial intelligence. His research interests are related with the automatic ocean satellite images interpretation and analysis and in computer vision.