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AN EXPERT SYSTEM FOR INTERPRETING MESOSCALE FEATURES IN OCEANOGRAPHIC SATELLITE IMAGES*

N. KRISHNAKUMAR and S. SITHARAMA IYENGAR

*Department of Computer Science
Louisiana State University
Baton Rouge, LA 70803, USA*

RON HOLYER and MATTHEW LYBANON

*Remote Sensing Branch
Naval Oceanographic and Atmospheric Research Laboratory
Stennis Space Center, MS 39529, USA*

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Thermal infrared images of the ocean obtained from satellite sensors are widely used for the study of ocean dynamics. The derivation of mesoscale ocean information from satellite data depends to a large extent on the correct interpretation of infrared oceanographic images. The difficulty of the image analysis and understanding problem for oceanographic images is due in large part to the lack of precise mathematical descriptions of the ocean features, coupled with the time varying nature of these features and the complication that the view of the ocean surface is typically obscured by clouds, sometimes almost completely. Towards this objective, the present paper describes a hybrid technique that utilizes a nonlinear probabilistic relaxation method and an expert system for the oceanographic image interpretation problem. This paper highlights the advantages of using the contextual information in the feature labeling algorithm. The need for an expert system and its feedback in automatic interpretation of oceanic features is discussed. The paper presents some important results of the series of experiments conducted at the Remote Sensing Branch, of the Naval Oceanographic and Atmospheric Research Laboratory, on the National Oceanic and Atmospheric Administration Advanced Very High Resolution Radiometer (AVHRR) imagery data. The results clearly indicate the drastic improvement in labeling due to the oceanographic expert system.

Keywords: Expert system; Knowledge-based system; Feature labeling; Oceanic features; Relaxation; Infrared imagery.

1. INTRODUCTION

Satellite-borne sensors potentially offer many advantages for the study of oceanic processes. They provide global synoptic measurements of various oceanic surface properties, in contrast to the local measurements, possibly at a range of depths, provided by conventional oceanographic measurement techniques. Thermal infrared (IR) images of the ocean obtained from satellite sensors are widely used for the study of ocean dynamics. Figure 1 shows a sample infrared image of the Gulf Stream

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Fig. 1. Typical IR image.

obtained from the Advanced Very High Resolution Radiometer (AVHRR) aboard the NOAA-7 satellite. Brightness in this infrared image is inversely proportional to the ocean surface temperature (dark areas represent warmer temperatures and light areas represent colder temperatures). Vortices (areas of closed circulation) within this turbulent flow pattern are called *eddies*. The Gulf Stream and its associated eddies are examples of mesoscale features ("mesoscale" is the name commonly applied to the features existing on spatial scales of the order of 50 to 300 km). Mesoscale features are important to the study of ocean dynamics, to fisheries and to many other diverse interests.

Current image analysis techniques rely on human interpretation of the satellite imagery. Human interpretation is obviously varied in its level of expertise and is highly labor-intensive. With the proliferation of high volume AVHRR image applications, it becomes highly desirable for certain applications to move from the labor-intensive manual interpretation of infrared imagery towards the capability for automated interpretation of these images. The complete automation of the oceanographic image interpretation function is probably not feasible, but one can begin to address certain subsets of the problem with the present-day image processing and artificial intelligence techniques. This was the motivation for the work reported by Lybanon *et al.*,¹ in the development of a prototype oceanographic expert system.

Several previous studies have addressed the automation of the analysis of infrared satellite imagery for mesoscale features. Gerson and Gaborski,² and Gerson *et al.*³ investigated the detection of the Gulf Stream in infrared images from the Geostationary Operational Environmental Satellite (GOES). Gerson and Gaborski² used a hierarchical approach where 16×16 pixel (128×128 km) "frames" within the image were evaluated for the possibility of containing the Gulf Stream. Frames flagged as Gulf Stream possibilities were then further evaluated to determine the exact location of the Stream within the frame by looking at statistics based on 5×5 pixel "local neighborhoods". As an outgrowth of the work reported in Refs. 2 and 3, Coulter⁴ performed automated feature extraction studies using the higher resolution Advanced Very High Resolution Radiometer data. Janowitz⁵ studied the automatic detection of the Gulf Stream eddies using Advanced Very High Resolution Radiometer data. Nichol⁶ used a region adjacency graph to define spatial relationships between elementary connected regions of constant gray level called atoms. Although satisfactory emulation of human extraction of eddy structure is claimed for this method, Nichol⁶ did point out that not all enclosed uniform areas identified by the method will correspond to real ocean structure. Krishnakumar *et al.*⁷ had earlier approached this problem and shown some preliminary results on the relaxation-based feature labeling scheme, the development of a prototype expert system and the interface between these two modules. Goodenough *et al.*⁸ have developed an expert system for remote sensing applications. In Ref. 8 the knowledge is presented in the production rules and frame databases. The expert system given in Ref. 8 is used to study the spatial differences between maps and images.

2. MOTIVATION OF THE PRESENT WORK

Our primary objective is to build a powerful automatic image interpretation system for oceanographic satellite images. In order to make this difficult problem tractable, we divide the problem into two parts: *the feature labeling problem* and *the development of an expert system*. It is clear that the performance of the labeling algorithm depends heavily on the low level image processing algorithms. Particularly, the output of an edge detector algorithm plays a major role in the feature labeling process. In view of this, a new efficient edge detector algorithm proposed by Holyer and Peckinpaugh⁹ is employed in our feature labeling technique. It is known that the conventional edge derivative operators are very sensitive to noise and are not suitable for analyzing oceanographic satellite images. The new edge detector algorithm proposed by Holyer and Peckinpaugh⁹ is based on the gray level co-occurrence matrix, which is commonly used in image texture analysis. This algorithm⁹ is found to exhibit the characteristics of fine structure rejection while retaining edge sharpness. In this paper we focus on the importance of an expert system in building an automatic oceanographic image interpretation system.

The objective of an oceanographic expert system is to correctly interpret the dynamics of the ocean process with minimal human interaction. Towards this objective, the development of a powerful oceanographic expert system is under way at

the Remote Sensing Branch of the Naval Oceanographic and Atmospheric Research Laboratory (NOARL). However, we have already developed a prototype expert system for Gulf Stream regional dynamics.¹ One of the elements of an expert system is a database of knowledge about the subject matter, with the knowledge represented in a form suitable for manipulation by the "inference engine" of the expert system (i.e. the logical and heuristic procedures for solving problems in the problem domain). With the help of the knowledge gained from discussions at NOARL and from the literature in oceanography, a knowledge base about the nature of the mesoscale features (occurrence, mean lifetime, movement, etc.) was built.¹

This paper describes a hybrid technique to label features in thermal infrared images obtained from satellites. The technique presented here exploits the advantages of using contextual information in the labeling algorithm. The remainder of the paper is organized as follows: Section 3 gives an overview of the architecture of the proposed image interpretation system. Section 4 introduces the probabilistic relaxation scheme and briefly discusses the application of this scheme to the oceanographic labeling problem. In Sec. 4.1 we develop a mathematical framework which is necessary for our labeling problem. Section 4.2 discusses the performance of our technique and describes the steps that are involved in implementing this technique. Section 5 describes the need for an oceanographic expert system and the implementation of the expert system. The improvement in feature labeling due to the feedback from the expert system is illustrated in Sec. 6 with the help of an example. Section 7 concludes with all the important features of this technique and proposes future extensions to the available scheme.

3. ARCHITECTURE OF THE INTERPRETER

In this section, we briefly describe the various components involved in the image iteratively updated using the nonlinear probabilistic relaxation scheme. Finally, the architecture of the proposed system. The IR image obtained from the satellite is the input to the feature labeling module. The feature labeling module consists of two submodules: one estimates the initial feature probabilities and the other implements the iterative updating scheme. The initial pixel probabilities are assigned with the help of the previous analysis and the ground truth data. These probability values are then iteratively updated using the nonlinear probabilistic relaxation scheme. Finally, the relevant features that are present in the image are labeled with the aid of a decision process.

The labeled features are then fed to the expert system module. This expert system is divided into two submodules. The first submodule consists of a knowledge base and an inference engine. The knowledge base has a thorough collection of facts and rules about the mesoscale features such as Gulf Stream, warm core rings, etc. Based on the positional information obtained from the feature labeling module and the knowledge base, the inference engine attempts to interpret the dynamics of these features. Basically the inference engine is a pattern matching module. The second submodule

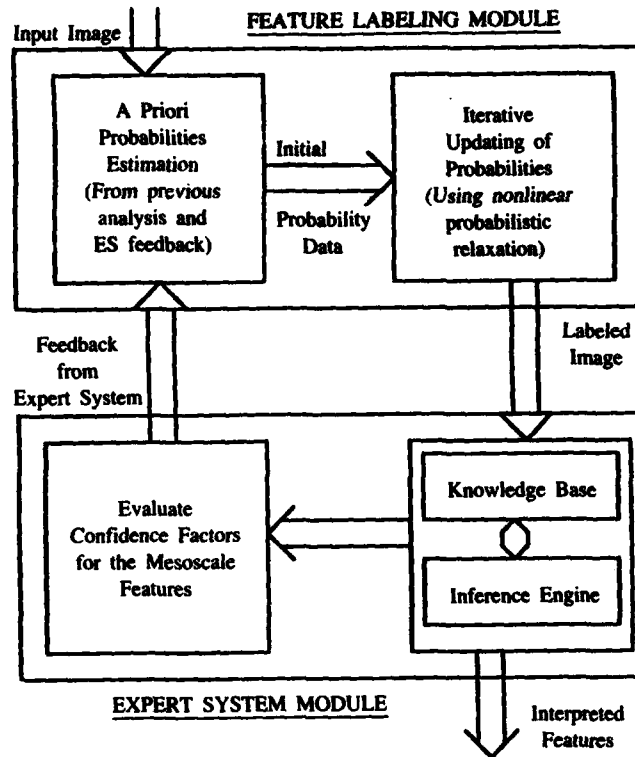


Fig. 2. Architecture of the hybrid system.

evaluates the consistency of the labeling process with the help of the knowledge base as well as from the input from the operator. This evaluation results in assigning a confidence factor to each of the features detected. This factor is then "fed back" to the feature labeling module, in addition to the previous data analysis, to improve the consistency of the labeling process in future.

A salient feature of this hybrid architecture is the feedback from the knowledge-based system to the labeling module. Due to atmospheric effects like cloud cover, the oceanic features may not be identified by the feature labeling module. Thus, the position of the Gulf Stream and eddies may not be determined correctly. In such cases, the expert system provides an approximate position of these features. This helps in interpreting the subsequent images. This is illustrated with the help of an example in Sec. 6. Another feature is the dynamic interpretation of the features. The hybrid architecture allows the expert system to learn from previous analysis. Also the modular approach allows the user to maintain the system and incorporate changes without much difficulty.

4. PROBABILISTIC RELAXATION LABELING

An important research area in image analysis and image interpretation technology is the development of methods that blend contextual information with conventional image processing algorithms. A literature survey clearly indicates that such a hybrid approach yields good results. Relaxation labeling is one such process. Relaxation labeling has been applied to a variety of image processing problems, e.g. linear feature enhancement,¹⁰ edge enhancement,¹¹ image enhancement,¹² pixel classification.^{13,14} A recent survey article by Kittler and Illingworth¹⁵ on relaxation labeling highlights the importance of this area of research. The survey¹⁵ also points out the advantages and possible applications of relaxation methods. More importantly, the relaxation labeling approach was elegantly described by Rosenfeld *et al.*¹⁶ who investigated the problem of labeling the sides of a triangle and proposed a set of schemes to solve the problem. The paper¹⁶ concluded with the result that the nonlinear probabilistic relaxation schemes yield better results than the others. The labeling algorithm presented in this paper is based on the nonlinear probabilistic relaxation technique.

The goal of the relaxation process is to reduce the uncertainty (and improve the consistency) in the assignment of one of the labels to each object in a set of related objects. In the oceanographic feature classification problem, the classes are the various oceanographic features, namely the north and south walls of the Gulf Stream, cold eddy, warm eddy, shelf front and coastal boundary. Refer to Fig. 3 to identify the positions of these oceanic features in a typical image. The objects are the individual pixels in a set of registered multi-temporal images. The uncertainty could be due to cloud cover or the overlap of features, features not belonging to one of the classes, noise in the image, or other factors. In this paper, we are attempting to label mesoscale features, but the ocean exhibits variability on all spatial scales. Thermal structure on scales smaller than mesoscale will interfere with the mesoscale feature labeling process. The underlying mathematical framework necessary for the relaxation labeling method is described in the next section.

4.1. Mathematical Framework For Relaxation Labeling

Let $\Lambda = \{\lambda_1, \lambda_2, \dots, \lambda_m\}$ be the set of possible labels that may be assigned to each pixel x in the IR image. Also we let $p_{\lambda}^k(x)$ denote the probability that the pixel at $x(i, j)$ belongs to the object λ after k iterations of the relaxation algorithm. Note that the probabilities are functions of time unlike the conventional pixel relaxation labeling schemes where the probability is a function of position alone. This allows the relaxation labeling algorithm to utilize temporal continuity to reduce the ambiguity in labeling. The ambiguity may arise due to noise (cloud cover, for example).

There are two steps in executing the probabilistic relaxation algorithm. In the first step, *a priori* probabilities are evaluated with the help of ground truth data and/or a previous but recent mesoscale analysis. In the second step, these *a priori* probabilities are iteratively updated (relaxation) until a consistent labeling is reached. We now discuss these two steps in detail.

Step 1. Estimating the a priori probabilities.

Let $p_{\lambda}^0(x)$ denote the *a priori* value, that is, the probability that pixel $x(i, j)$ belongs to the object λ at the zeroth iteration. The Bayesian probability equation is used to evaluate this value. Equation (4.1.1) is used to calculate $p_{\lambda}^0(x)$.

$$p_{\lambda}^0(x) = \frac{p(x|\lambda) P(\lambda)}{\sum_{\lambda} p(x|\lambda) P(\lambda)} \quad (4.1.1)$$

where $p(x|\lambda)$ denotes the conditional density function and $P(\lambda)$ the probability of occurrence of the object λ .

To evaluate the conditional density function $p(x|\lambda)$, a set of parameters is measured at the pixel $x(i, j)$. Let X denote the parameter vector. The following parameters are used to form the vector X :

- (1) the vector from origin to pixel $x(i, j)$ (both the magnitude and direction).
- (2) gray scale intensity value at the pixel $x(i, j)$.
- (3) the edge magnitude (Sec. 4.2 presents the chosen edge operator algorithm).

For each object, the mean vector μ_{λ} and the covariance matrix $\sum_{\lambda}$ are computed. Also it is assumed that the conditional density function follows a normal distribution. Hence the conditional density function $p(x|\lambda)$ is evaluated using Eq. (4.1.2).

$$p(x|\lambda) = (2\pi|\sum_{\lambda}|)^{-1/2} \exp\left\{-\frac{1}{2} (X - \mu_{\lambda})' \sum_{\lambda}^{-1} (X - \mu_{\lambda})\right\}. \quad (4.1.2)$$

To compute $P(\lambda)$, relative areas of the objects are considered. The number of pixels in the object λ is n_{λ} . Then $P(\lambda)$ can be calculated using Eq. (4.1.3).

$$P(\lambda) = \frac{n_{\lambda}}{\sum_{\lambda} n_{\lambda}}. \quad (4.1.3)$$

Step 2. Iterative updating algorithm.

We now discuss the probability updating rule. The new estimate of the probability of λ at $x(i, j)$ is given by (4.1.4).

$$p_{\lambda}^{k+1}(x) = \frac{p_{\lambda}^k(x) (1 + q_{\lambda}^k(x))}{\sum_{\lambda} p_{\lambda}^k(x) (1 + q_{\lambda}^k(x))} \quad (4.1.4)$$

where $q_{\lambda}^k(x)$ is called the update factor.

The updating factor for the estimate $p_{\lambda}^k(x)$ at the k th iteration is given by Eq. (4.1.5).

$$q_{\lambda}^k(x) = \frac{1}{m} \sum_y \sum_{\lambda'} r_{\lambda\lambda'}(x, y) p_{\lambda'}^k(y) \quad (4.1.5)$$

where m is the number of objects. In this equation, $r_{\lambda\lambda'}(x, y)$ denotes compatibility coefficients. These coefficients are computed as in Refs. 14 and 16. According to the relaxation scheme, $r_{\lambda\lambda'}(x, y)$ is a measure of the probabilistic compatibility between label λ on point x and label λ' on point y , and has the following characteristics:

- (1) If λ on x frequently co-occurs with λ' on y , then $r_{\lambda\lambda'}(x, y) > 0$, and if they always co-occur, then $r_{\lambda\lambda'}(x, y) = 1$.
- (2) If λ on x rarely co-occurs with λ' on y , then $r_{\lambda\lambda'}(x, y) < 0$, and if they never co-occur, then $r_{\lambda\lambda'}(x, y) = -1$.
- (3) If λ on x occurs independently of λ' on y , then $r_{\lambda\lambda'}(x, y) = 0$.

4.2. Discussion of the Technique

The implementation of the above mentioned technique is carried out in two stages.

Stage 1

At the first stage, *a priori* probabilities are estimated using a manually prepared mesoscale analysis from a time period of two days prior to the test image. The objects present in the oceanographic IR image are identified with the help of previous analysis. A set of pixels on the north and south wall of the Gulf Stream are provided by the previous analysis. The center pixel and radii of the eddies are also given. From the parameter vector X for a pixel $x(i, j)$, the mean vector μ_λ is calculated. Also for each object λ , the covariance matrix $\sum_\lambda$ is computed. Equation (4.1.2) is used to compute the conditional density function $p(x|\lambda)$. Finally the initial probability $p_\lambda^0(x)$ is computed using Eq. (4.1.1).

Stage 2

In the second stage, the iterative updating rule is implemented. The compatibility coefficients are calculated using the initial class probability values obtained in the first stage. These are fixed during the update process. As a concluding step in the second stage of the implementation, the iterative updating algorithm is implemented using Eq. (4.1.4). The iterative algorithm terminates when $(p_\lambda^{k+1}(x) - p_\lambda^k(x)) < \epsilon$, where ϵ is a very small quantity.

Now we discuss the features of the edge detection algorithm proposed by Holyer and Peckinpaugh.⁹ The motivation behind the development of such a new edge detector algorithm is to aid the analysis of oceanographic satellite images. The popular derivative-based edge operators, viz. Sobel's operator, are shown to be too sensitive to edge fine-structure and to weak gradients to be useful in this application. The edge algorithm proposed by Holyer and Peckinpaugh⁹ is based on the cluster shade texture measure, which is derived from the gray level co-occurrence (GLC) matrix. Holyer and Peckinpaugh⁹ have suggested that the edge detection technique based on the GLC matrix can be effectively used in automated detection of mesoscale features. The (i, j) th element of the GLC matrix, $P(i, j|\Delta x, \Delta y)$, is the relative frequency with which two image elements, separated by distance $(\Delta x, \Delta y)$, occur in the image, one with intensity level i and the other with intensity level j . The elements of the GLC matrix can be combined in many different ways to give a single numerical value that

would be a measure of the edges present in the image. Holyer and Peckinpaugh⁹ have used a cluster shade function which is found to be very effective in the edge detection process. The new edge algorithm computes the cluster shade function at each pixel. Then the edges are detected by finding the significant zero crossings in the cluster shade image. The advantages of this new edge algorithm over the conventional derivative-based techniques are discussed in Ref. 9. It is known that using large windows in derivative-based edge detector algorithms results in poor smoothing. This problem is circumvented in the new algorithm. Because edges are detected by finding zero crossings, precisely positioned lines result, even if the GLC matrix is calculated using a larger window. So, the desired edge detection characteristic of retaining sharp edges while eliminating edge detail is achieved with the help of the new algorithm. As an input to our feature labeling algorithm, we used the image output generated by cluster shade algorithm, with a window size of 16×16 pixels and zero crossing threshold of 50. The edge magnitudes obtained from this new edge detector algorithm are used as an input to the feature labeling algorithm. In particular the edge magnitudes are used to evaluate *a priori* probability values.

5. OCEANOGRAPHIC EXPERT SYSTEM

The Remote Sensing Branch of NOARL studies and develops methods to exploit satellite data to provide oceanographic information. The Navy needs to provide such information to the Fleet, so NOARL has an objective of transforming research techniques for the oceanographic interpretation of satellite data into operational procedures. From a large volume of satellite data, combined with non-satellite data, the shipboard user will be required to produce operationally useful tactical products. Dramatic improvement will be required in our ability to automate the image analysis process.

Interactive image processing is a powerful tool in the hands of an expert image interpreter. However, human interpretation is both varied in its level of expertise and is labor-intensive. Expert judgement is required for oceanographic image interpretation because there is little or no standardization in either image enhancement or interactive techniques. NOARL has conducted research in the use of concepts from the field of artificial intelligence to develop knowledge-based "expert systems" to automate some aspects of the oceanographic image interpretation task. That work is an attempt to remove human-labor-intensive and varying-skill-level elements from the interpretation of oceanographic image and other satellite data. Lybanon *et al.*¹ describe the motivation and some of the history of NOARL in this area.

The rule base of the expert system is derived from an unprecedented compilation of information, and the expert system's mode of operation is innovative. The rule base represents oceanographic knowledge about the evolution of mesoscale ocean features in the Gulf Stream region of the north Atlantic Ocean. The rules are applied in such a way that the expert system describes the kinematics of that evolution. The expert system is presently implemented in a combination of OPS83, C, and FORTRAN running on a VAX 8300. The expert system uses the rules about the features to evolve

an initial "state" to a later time. The new, hypothesized state can then be used as a new initial condition and the process is repeated. This process can be usefully carried out for several steps. This mode of operation is different from expert systems which use a (sometimes lengthy) chain of reasoning to reach a single conclusion, such as a system for medical diagnosis.

The domain of the expert system is the Gulf Stream region of the north Atlantic Ocean. The expert system has different rules for ring and Gulf Stream behavior in each of nine geographical regions. Figure 3 shows the operating regions of the expert system. Aside from the lines that separate them, the regions are bounded only by land. A ring's behavior as hypothesized by the expert system depends upon which region its center is in at the beginning of a time step. Basically, the motion has a region-dependent velocity vector. However, a ring that is closer than a certain critical distance from the Gulf Stream undergoes a modification of the basic motion. The Gulf Stream interaction rules are also region-dependent. The details depend upon how close the ring is to the Gulf Stream; the Gulf Stream interaction may result in a deflection or a looping motion of the ring, with possible coalescence with the Stream in some cases. Ring sizes decrease with time. The rate of decrease depends on the region and on whether there is Gulf Stream interaction. A ring that shrinks below a certain size disappears. Gulf Stream motion is modeled as downstream propagation of meanders, with region-dependent phase velocities and amplitude factors. While this is only a first-order model, there is justification in the literature for this behavior. Refer to Ref. 1 for a complete description of the expert system.

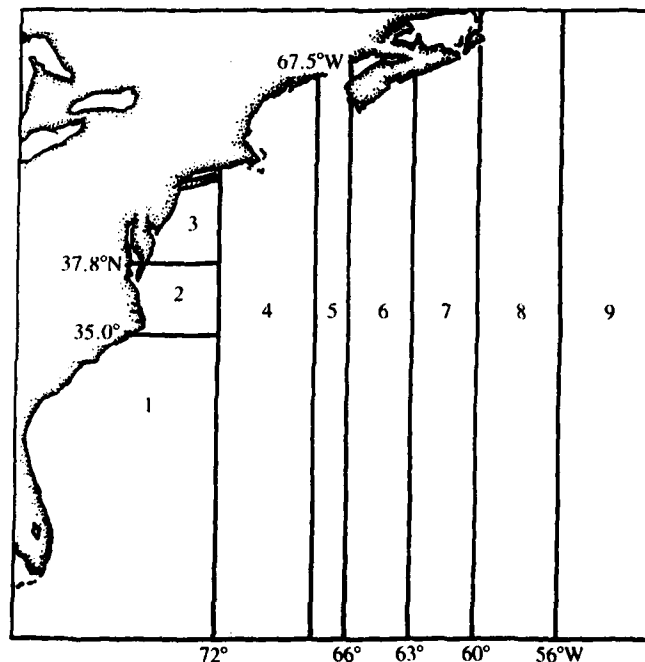


Fig. 3. Nine regions of expert system domain.

6. HYBRID FEATURE LABELING TECHNIQUE—AN EXAMPLE

In this section we present the results of our feature labeling technique. We show that the expert system greatly helps in labeling the features when the analysis of the previous sample image fails. This situation arises when the oceanic features are completely covered by cloud. In the following we describe the steps involved in the hybrid feature labeling technique.

The system starts up with the human interpretation of an image that is obtained two or three days before the current image. The initial probabilities are computed based on the analysis of the previous image. Nonlinear probabilistic relaxation technique is applied to label the features in the current image. Figure 1 shows the IR image with all the features. The output of the edge detector algorithm is given in Fig. 4. Figure 5 shows the IR image with all the edge features overlapped. The positional details of the features are then given to the expert system. Sometime the IR image of the ocean may not be clear. That is, the features are covered by cloud. To analyze such an image, the feedback from the expert system is used. The position of the oceanic features is obtained by activating the inference engine of the expert system. This approach is different from the conventional one, in which the information is always provided by the low level module. The concept of getting feedback from a high level module (like an expert system) is totally new and justified in automatic image interpretation of oceanographic images. The output of the labeling algorithm is given in Fig. 6.



Fig. 4. Output of the edge detector.



Fig. 5. IR Image with edges overlapped.

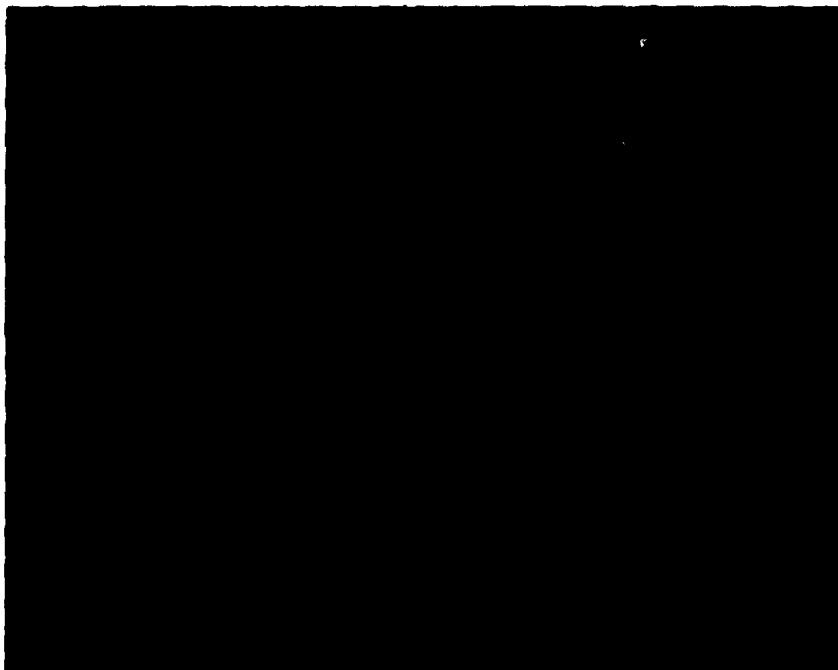


Fig. 6. Output of the feature labeling algorithm.

7. SUMMARY AND RECOMMENDATIONS FOR FUTURE WORK

In this paper, the need for automatic interpretation of oceanographic images is emphasized. The advantage of exploiting the contextual information in feature labeling is highlighted. An efficient and simple technique for labeling of oceanic features is described. The underlying theoretical framework and the steps involved in estimating the probability functions are explained in detail. The overall architecture of the proposed image interpretation system is presented. The usefulness of an expert system in feature labeling is discussed. The concept of getting feedback from the expert system is a new approach and it is explained with the help of an example.

As a future extension to the present work we propose to:

- (i) make the oceanographic expert system "learn" from its past experience in analyzing the satellite imagery data.
- (ii) investigate the possibility of implementing a parallel relaxation labeling algorithm to speed up the labeling process.

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Narayanan Krishnakumar received the B.S. degree in applied sciences from Madurai University, India in 1981 and the B.S. degree in electrical and electronics engineering from the Indian Institute of Science, Bangalore, India in 1984. He is currently a

Ph.D. candidate at Louisiana State University.

His primary research interests are in the areas of computer vision, digital image analysis, artificial intelligence, and parallel processing.

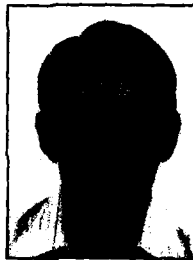


S. Sitharama Iyengar directs the Robotics Research Laboratory (RRL) at Louisiana State University. His area of research interest is in the design and analysis of algorithms for a wide variety of problems. Professor Iyengar's research at the RRL addresses problems

that are fundamental to the implementation of autonomous intelligent machines. This research is comprehensive, covering most aspects of intelligent systems. For example, he has conducted important work on the problems of intelligent robot navigation, intelligent sensing, world-modeling using acoustic sensors, and real-time expert systems for the control of mobile robots, to name a few. Many of these projects have involved collaboration with NASA, Oak Ridge National Laboratory, Navy-NORDA, and JPL/Caltech.

Professor Iyengar has published over 100 papers in refereed journals and conference proceedings. He has served as a visiting research scientist at the Robotics and Artificial Intelligence Group, CESAR Division, Oak Ridge National Laboratory, as a member of the National Science Foundation select panel for reviewing research proposals on neural networks, as Guest

Editor for a special issue on Autonomous Systems in *IEEE Transactions on Computers*, June 1989, and as Guest Editor for a special issue on Intelligent Image Databases in *IEEE Transactions on Software Engineering*, May 1988. He is presently a Guest Editor for a special issue on Distributed Sensor Networks in *IEEE Transactions on Systems, Man and Cybernetics*. He has won several research and teaching awards and is a senior IEEE member.



Ronald J. Holyer received the B.A. degree in physics and mathematics from Augustana College in 1964, the M.S. degree in physics from the South Dakota School of Mines and Technology in 1966, and the Ph.D. degree in geology from the University of

South Carolina in 1989.

He has conducted remote sensing and image processing research at Texas Instruments, Inc. and Lockheed Electronics Co., Inc. He is presently with the Naval Oceanographic and Atmospheric Research Laboratory at the Stennis Space Center, Mississippi, where he is a principal investigator in the field of automated image analysis and pattern recognition applied to remotely sensed oceanographic data.



Matthew Lybanon received the B.S. and M.S. degrees in physics from Georgia Institute of Technology, Atlanta, in 1960 and 1962 respectively. He has conducted research in remote sensing, image processing and pattern recognition while employed by the Computer Sciences Corporation at NASA's Marshall Space Flight Center and Stennis Space Center. A

member of the Naval Oceanographic and Atmospheric Laboratory's Remote Sensing Branch, he is Principal Investigator for the GEOSAT Ocean Applications Program, for a project which is developing knowledge-based techniques for the automated interpretation of oceanographic satellite data, and for a project to provide analysis tools for Navy oceanographic centers. His current professional interests include artificial intelligence, neural networks, image processing, generalized nonlinear least squares methods, and applications of those topics to the extraction of information on ocean dynamics and sea ice from satellite observations.

Mr. Lybanon is a member of the American Physical Society and the American Geophysical Union. He is a reviewer for papers submitted to the American Journal of Physics. He was awarded a NASA commendation for image processing work to help assess the damage to Skylab's solar panel when they opened prematurely during launching.

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