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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 technique that utilizes a non-linear probabilistic relaxation method for the oceanographic feature labeling problem. A unified mathematical framework that helps in solving the problem is presented. This paper highlights the advantages of using the contextual information in the feature labeling algorithm. The feature labeling technique makes use of an new, efficient edge detection algorithm based on cluster shade texture measure. This new algorithm is found to be more suitable for labeling the mesoscale features present in the oceanographic satellite images. The paper presents some important results of the series of experiments conducted at Remote Sensing Branch, NORDA on the NOAA AVHRR imagery data. The paper concludes with a motivation for using this technique to build an oceanographic expert system.

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A TECHNIQUE FOR FEATURE LABELING IN INFRARED OCEANOGRAPHIC IMAGES

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ABSTRACT

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 technique that utilizes a non linear probabilistic relaxation method for the oceanographic feature labeling problem. A unified mathematical framework that helps in solving the problem is presented. This paper highlights the advantages of using the contextual information in the feature labeling algorithm. The feature labeling technique makes use of a new, efficient edge detection algorithm based on cluster shade texture measure. This new algorithm is found to be more suitable for labeling the mesoscale features present in the oceanographic satellite images. The paper presents some important results of the series of experiments conducted at Remote Sensing Branch, NORDA on the NOAA AVHRR imagery data. The paper concludes with a motivation for using this technique to build an oceanographic expert system.

Key words: feature labeling, feature extraction, oceanic features, edge detection, knowledge based systems, relaxation, infrared imagery.

1.0 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 images of the ocean obtained from satellite sensors are widely used for the study of ocean dynamics. Fig.1 shows a sample infrared image of the Gulf-Stream 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, the 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 Advanced Very High Resolution Radiometer image applications , it becomes highly desirable for certain applications to move from the labor-intensive manual interpretation of infrared imagery towards a 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] [15], in the development of a prototype oceanographic expert system.

Several previous studies have addressed the automation of the analysis of the infrared satellite imagery for mesoscale features. Gerson and Gabroski [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 Gabroski [2], used a hierarchical approach where 16x16 pixel (128x128 km) "frames" within the image were evaluated for the possibility of

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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 5x5 pixel "local neighborhood". As an outgrowth of the work reported in [2] and [3], Coulter [4] performed automated feature extraction studies using the higher resolution Advanced Very High Resolution Radiometer data. Janowitz [5] studied the automatic detection of the Gulf Stream eddies using the Advanced Very High Resolution Radiometer data. Nichol [6] uses a region adjacency graph to define spatial relationships between elementary connected regions of constant gray level called atoms. Eddy-like structure is then identified by searching the graph for isolated atoms of high temperature that are enclosed by atoms of lower temperature (for the case of warm eddies). Although satisfactory emulation of human extraction of eddy structure is claimed for this method, Nichol[6] does point out that not all enclosed uniform areas identified by the method will correspond to real ocean structure.

2.0 MOTIVATION OF THE PRESENT WORK

In this section we present the motivation behind 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 : feature labeling problem and the development of an expert system. In this paper we focus on the feature labeling problem. 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 Peckinpaugh [7] 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 Peckinpaugh [7] is based on the gray level co-occurrence matrix, which is commonly used in image texture analysis. This algorithm [7] is found to exhibit the characteristics of fine structure rejection while retaining edge sharpness. In this paper we focus on the preliminary results of a feature labeling algorithm and the effect of the cluster shade edge detector algorithm on the performance of the labeling. In the following paragraph we briefly outline the various steps taken to solve the second sub problem.

The objective of an expert system for oceanographic 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 in the process of development at Remote Sensing Branch, NORDA. We have already developed a prototype expert system for Gulf Stream regional dynamics [1]. The current activities focus on building an expert system that makes use of the information about the position of mesoscale features obtained from the relaxation labeling scheme. One element 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 NORDA and from the literature in oceanography, a knowledge base about the nature of the mesoscale features (occurrence, mean life time, movement, etc.) was built [1]. Presently, we are in the process of designing an expert system which makes use of the positional information about the features(obtained from the relaxation labeling) and the knowledge base of mesoscale information.

This paper presents a relaxation labeling scheme to label features in thermal infrared images obtained from satellite. The technique presented in this paper exploits the advantages of using the contextual information in the labeling algorithm. The remainder of the paper is organized as follows: Section 3.0 introduces the probabilistic relaxation scheme and briefly discusses the application of this scheme to the oceanographic labeling problem. In section 4.0 we develop a mathematical frame work which is necessary for our labeling problem. Section 5.0 discusses the performance of our technique and describes the steps that are involved in implementing this technique. Section 6.0 gives a brief description on the implementation of this technique on the image analysis system at NORDA. Section 7.0 concludes with all the important features of this technique and future extensions to the available scheme.

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3.0 RELAXATION PROCESS

An important research area in image analysis and image interpretation technology is the development of methods that blend contextual information with the conventional image processing algorithms. The literature survey clearly indicates that such a hybrid approach yields good results. Relaxation labeling is one such process that approaches this problem. Relaxation labeling has been applied to a variety of image processing problems eg., linear feature enhancement [8], edge enhancement [9], image enhancement [10], pixel classification [11,12]. Recently a survey article by Kitten and Illingworth [13] on relaxation labeling highlights the importance of this area of research. The survey [13] also points out the advantages and possible applications of relaxation methods. More importantly, the relaxation labeling approach was elegantly described by Rosenfeld et al. [14] who investigated the problem of labeling the sides of a triangle and proposed a set of schemes to solve the problem. The paper [14] concluded with the result that the non linear probabilistic relaxation schemes yield better results than the others. The labeling algorithm presented in this paper is based on the non linear 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 North and South wall of Gulf Stream, cold eddy, warm eddy, shelf front and coastal boundary. Refer to fig.2 to identify the position 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 the cloud cover or the overlap of the features that are mentioned above, 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 of the paper.

4.0 MATHEMATICAL FRAMEWORK

Let $\Lambda = \{\lambda_1, \lambda_2, \ldots \lambda_m\}$ be the set of possible labels that may be assigned to each pixel x in the IR image Also we let $p_\lambda^k(x,t)$ denote the probability that the pixel at x(i,j) and time instant t, 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. At 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 $p_\lambda^0(x,t)$ denote the a priori value, that is, the probability that pixel **x(i,j)** at time t belongs to the object λ, at the zeroth iteration. The Bayesian probability equation is used to evaluate this value. The equation (4.1) is used to calculate $p_\lambda^0(x,t)$.

$$p_\lambda^0(x,t) = \frac{p(x,t \mid \lambda)\ P(\lambda)}{\Sigma_\lambda\ p(x,t \mid \lambda)\ P(\lambda)} \qquad (4.1)$$

where $p(x,t \mid \lambda)$ denote the conditional density function and $P(\lambda)$ the probability of occurrence of the object λ.

To evaluate the conditional density function $p(x,t \mid \lambda)$, 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) distance of the pixel **x(i,j)** from the origin, both the magnitude and direction.
(2) gray scale intensity value at the pixel **x(i,j)**.
(3) the edge magnitude (Section 5.1 presents the chosen edge operator algorithm).

For each object, the mean vector μ_λ and the covariance matrix Σ_λ are computed. Also it is assumed that the conditional density function follows a normal distribution. Hence the conditional density function $p(x,t \mid \lambda)$ is evaluated using equation (4.2).

$$p(x,t \mid \lambda) = (2\pi \mid \Sigma_\lambda \mid)^{-1/2} \exp\left\{ -\frac{1}{2}\ (X-\mu_\lambda)' \Sigma_\lambda^{-1} (X-\mu_\lambda) \right\} \qquad (4.2)$$

To compute $P(\lambda)$, relative areas of the objects are considered. The number of pixels in the object λ be n_λ. Then $P(\lambda)$ can be calculated using equation (4.3).

$$P(\lambda) = \frac{n_\lambda}{\Sigma_\lambda n_\lambda} \qquad (4.3)$$

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 (4.4).

$$p_\lambda^{k+1}(x,t) = \alpha_\lambda \frac{p_\lambda^k(x,t)\,(1+q_\lambda^k(x))}{\Sigma_\lambda p_\lambda^k(x,t)\,(1+q_\lambda^k(x))} + (1-\alpha_\lambda)\, p_\lambda(x,t') \qquad (4.4)$$

where $q_\lambda^k(x)$ is called the update factor and α_λ is called temporal weighting function.

The method of estimating these factors are illustrated below. The updating factor for the estimate $p_\lambda^k(x,t)$ at the kth iteration is given by equation (4.5).

$$q_\lambda^k(x) = \frac{1}{m} \Sigma_y \Sigma_{\lambda'} r_{\lambda\lambda'}(x,y)\, p_{\lambda'}^k(y) \qquad (4.5)$$

where m is the number of objects. In this equation, $r_{\lambda\lambda'}(x,y)$ denote compatibility coefficients. These coefficients are computed as in [13,16]. 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 $r_{\lambda\lambda'}(x,y) = 0$.

These compatibility coefficients are computed using the equation (4.6).

$$r_{\lambda\lambda'}(x,y) = \frac{cov(\lambda,\lambda')}{\sigma(\lambda)\ \sigma(\lambda')} \qquad (4.6)$$

where $cov(\lambda,\lambda')$ denotes the covariance of two events, namely, the pixel **x** is assigned the label λ and the pixel y is assigned the label λ' and is given as:

$$cov(\lambda,\lambda') = p(\lambda\&\lambda') - p(\lambda)p(\lambda') \qquad (4.7)$$

The joint probability $p(\lambda\&\lambda')$ can be calculated using the position vectors of the pixels **x** and **y**. Let m and m' be the mean position vectors of the objects λ and λ' respectively. Then the joint probability can be computed using simple functions as given by equations (4.8a) and (4.8b).

$$p(\lambda\ \&\ \lambda') = \frac{y - x}{m' - m} \qquad \text{if } \lambda \neq \lambda' \qquad (4.8a)$$

$$p(\lambda\ \&\ \lambda') = 1 - \frac{x - m}{x + m} \qquad \text{if } \lambda = \lambda' \qquad (4.8b)$$

The new estimate of the probability of λ at **x(i,j)** is :

$$p_\lambda^{k+1}(x,t) = \alpha_\lambda \frac{p_\lambda^k(x,t)\,(1+q_\lambda^k(x))}{\Sigma_\lambda p_\lambda^k(x,t)\,(1+q_\lambda^k(x))} + (1-\alpha_\lambda)\, p_\lambda(x,t') \qquad (4.9)$$

where $p_\lambda(x,t')$ denotes the probability value at the pixel **x(i,j)** at time instant t', $t' < t$ and α_λ denotes the temporal weighting function for the object λ. The function α_λ determines the weight that is given to the current probability values and the factor $(1-\alpha_\lambda)$ associates a weight to the probability values calculated at previous time instant t'.

To estimate the new probability value, either (a) the probability value at the previous time frame t' or (b) a set of probability values at time frames t', t'', t''' etc., can be used. In the present analysis and the implementation, the method (a) is chosen. Also it is proposed to implement the method (b) and compare improvements (if any) in the feature labeling. The temporal weighting function can be determined with the help of the previous analysis of the images. It is understood that this temporal weighting function can not be constant in the real time situation. For example in some cases, the performance of the labeling may be less satisfactory and correspondingly the temporal weighting function should be given a relatively smaller value. Hence the selection of this function itself may be a problem in some cases. One may use different values for this function and the performance of the labeling can be compared. The iterative updating is terminated when the difference between the probability values at the k th and the $(k + 1)$ th iterations is very small (say less than 0.1 %).

5.0 DISCUSSION ON THE TECHNIQUE

The implementation of the above mentioned technique is carried out in two stages. The flow chart shown in fig.4 depicts the various steps involved in implementing the technique.

At the first stage, the a priori probabilities are estimated using a manually prepared mesoscale analysis from a time period of five days prior to the test image.

The objects present in the oceanographic IR image are identified with the help of the previous analysis. The shapes (or boundaries) of these objects are then determined and represented by a regular polygon. The parameter values are then computed for all the pixels inside these polygons. A reasonably accurate algorithm which finds out whether a pixel is inside a polygon or not is implemented.

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 Σ_λ is computed. The equation (4.2) is used to compute the conditional density function $p(x,t \mid \lambda)$. Finally the initial probability $p_\lambda^0(x,t)$ is computed using the equation (4.1). The output of the first stage is shown in fig.3. The output image is split into six parts to illustrate the labeling. Fig.3.1 shows the output of the labeling module with all the five features labeled. Refer to fig.2 to compare the labeling with the hand segmented image. To illustrate the labeling process five different features are considered. They are : two parts of the north wall, south wall and two warm eddies. The labeling of these five features is shown in figures 3.2 to 3.6. The individual pixels in the oceanographic image are labeled depending on the initial probability values obtained in the first stage.

5.1 DISCUSSION ON CLUSTER SHADE EDGE ALGORITHM

In this section, we discuss the features of the edge detection algorithm proposed by Holyer and Peckinpaugh [7]. 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 [19] 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 Peckinpaugh [7] is based on the cluster shade texture measure, which is derived from the gray level co-occurrence matrix (GLC). The authors [7] 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 , $P(i,j \mid \Delta x, \Delta y)$ 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 could 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 Peckinpaugh [7] 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 [7]. 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 characteristics 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 16x16 pixels and zero crossing threshold of 50. The edge magnitudes obtained from this new edge detector algorithm is used as an input to the feature labeling algorithm. In particular the edge magnitudes are used to evaluate the a priori probability values. It can be seen from fig 3. that the only the edge pixels participate actively in the labeling process. Also the speed of the algorithm that computes the a priori probability values is greatly improved because of the reduced number of pixels for consideration.

In the second stage, the iterative updating rule is implemented. The compatibility coefficients are evaluated using the equation (4.6). The 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 the equation (4.9). The iterative algorithm terminates when $(p_\lambda^{k+1}(x,t) - p_\lambda^k(x,t)) < \varepsilon$ where ε is a very small quantity. Clearly the time parameter is helpful in reducing the ambiguity, especially when the image is contaminated with noise.

6.0 IMPLEMENTATION

In this section, we present the experimental results of the first stage of the relaxation labeling technique : estimating the a priori probability values of a reference image. The software that computes the a priori probabilities is developed on VAX 8300 system running the VMS operating system installed at the Remote Sensing Branch, NORDA. We used the Interactive Digital Satellite Image Processing System consisting of International Imaging System's S600 software with NORDA extensions to process the oceanographic satellite images. The software modules are developed in 'C' language. The positional information about the oceanographic features present in the image can be provided either manually or from the previous analysis of the satellite imagery data. The module first computes the mean vectors and covariance matrices for all the objects present in the reference image. The second part of the software module computes the a priori probability values as given by equation (4.1).

To illustrate the performance of the labeling algorithm, an oceanographic infrared image with some of the typical oceanic features is taken (refer to fig.1). The objects that are selected for labeling are north wall, south wall and warm eddies. The a priori knowledge about the objects, namely the position is taken from the prior analysis shown in fig.3 and given as an input to the labeling module. The a priori probability values are then computed for all the pixels present in the image. To highlight the performance of this initial labeling algorithm, a decision making algorithm based on these a priori probability values is implemented. A pixel that has a probability value above 0.8 for an object is given the label for that object. The decision algorithm selects the pixels in the neighborhood of the objects to illustrate the results obtained. The edges of the labeled objects are dilated for clear identification of the labels. The covariance matrices for the objects are shown in fig.5.

7.0 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 functions are explained in detail. Results of the first stage of the labeling technique are presented. The results and the performance analysis of the proceeding stages of the technique will appear in forthcoming issues. The first stage, namely, the estimation of a priori probabilities for the reference image, is complete and has been tested on real oceanographic images. An expert system that uses the knowledge base and the information obtained from the labeling algorithm is in the process of development.

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

(i) investigate the possibility of implementing a parallel relaxation labeling algorithm to speed up the labeling process.

(ii) make the oceanographic expert system "learn" from its past experience in analyzing the satellite imagery data.

(iii) incorporate additional information about the mesoscale features (size, physical properties, etc.) during the labeling process to reduce the ambiguity in labeling the features.

REFERENCES

1. M. Lybanon, J.D. McKendrick, R.E. Blake, J.R.B. Cockett and M.G. Thomason, *A prototype knowledge-based system to aid the oceanographic image analyst, SPIE Vol 635- Applications of Artificial Intelligence III*, 1986, 203-206.
2. D.J Gerson and P.Gaborski, *Pattern analysis for automatic location of oceanic fronts in digital satellite imagery, Naval Oceanographic Office*, TN 3700-65-77, October, 1977.
3. D.J. Gerson, E. Khedouri and P. Gaborski, *Detecting the gulf stream from digital infrared data pattern recognition, The Belle W. Baruch library in Marine Science*, No.12, 1982, 19-39.
4. R.E. Coulter, *Application of the Bayes decision rule for automatic water mass classification from satellite infrared data, Proc. 17th Int. Symposium on remote sensing of environment*, Vol II, 1983, 589-597.
5. M.F. Janowitz, *Automatic detection of gulf stream rings*, Technical report TR-J8501, Office of Naval Research, Contr N-00014-79-C-0629, June 1985.
6. D. G. Nichol, *Autonomous extraction of eddy-like structure from infrared images of the ocean, IEEE Trans. GeoScience and Remote Sensing*, 25, 1987, 28-34.
7. R.J. Holyer and S.H. Peckinpaugh, *Edge detection applied to satellite imagery of the oceans, To appear in IEEE Trans. GeoScience and Remote Sensing.*
8. S.W. Zucker, R.A. Hummel and A. Rosenfeld , *An application of relaxation labeling to line and curve enhancement, IEEE Trans.Computer*, 26, 1977, 399-403, 922-929.
9. B.J. Schachter, A. Lev, S.W. Zucker and A. Rosenfeld, *An application of relaxation methods to edge reinforcement. IEEE Trans.Syst.Man Cyber*, 7, 1977, 813-816.
10. L.S. Davis and A. Rosenfeld , *Noise cleaning by iterated local averaging, IEEE Trans. Syst. Man Cyber* , 8, 1978, 705-710.
11. J.O. Eklundh, H. Yamamoto and A. Rosenfeld, *A relaxation method in multispectral pixel classification, IEEE PAMI*, 2, 1980, 72-75.
12. L.S. Davis, C.Y. Wang and H.C. Xie, *An experiment in multispectral, multitemporal crop classification using relaxation techniques, Computer vision, Graphics and Image Processing*, 23, 1983, 227-235.
13. J. Kittler and J. Illingworth, *Relaxation labeling algorithms - a review, Image and Vision Computing*, 1985, 206-216.
14. A. Rosenfeld, R.A. Hummel and S.W. Zucker, *Scene labeling by relaxation operations, IEEE Trans. Syst. Man Cyber*, 6, 1976, 420-434.
15. M. Lybanon, *Oceanographic expert system knowledge base evaluation, NORDA Technical Note 350*, May 1987.
16. S. Peleg and A. Rosenfeld, *Determining compatibility coefficients for curve enhancement relaxation processes, IEEE Trans. Syst. Man Cyber*, 8, 1978, 548-555.

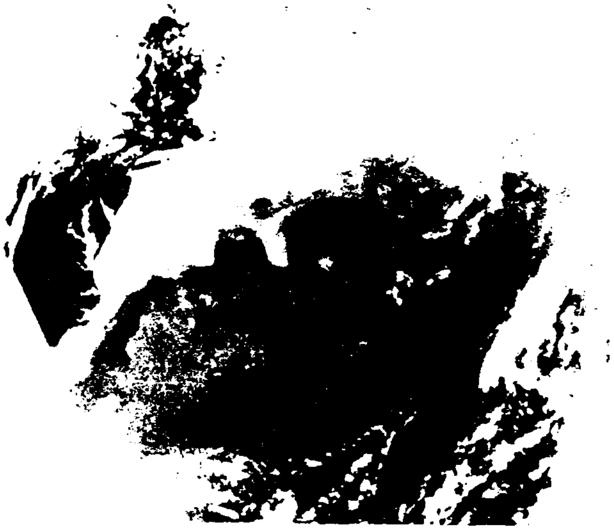

fig.1 sample IR image

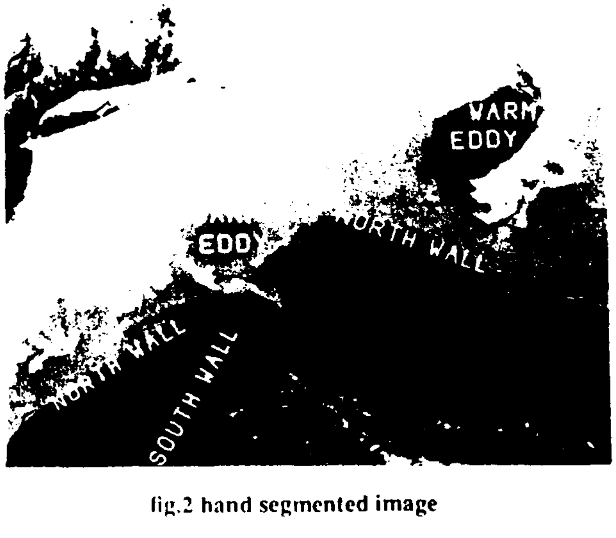

fig.2 hand segmented image

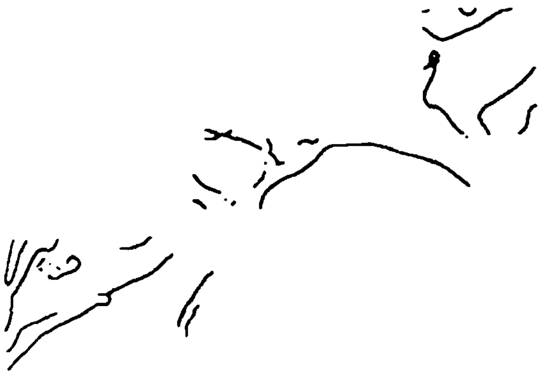

fig.3.1 labeled image

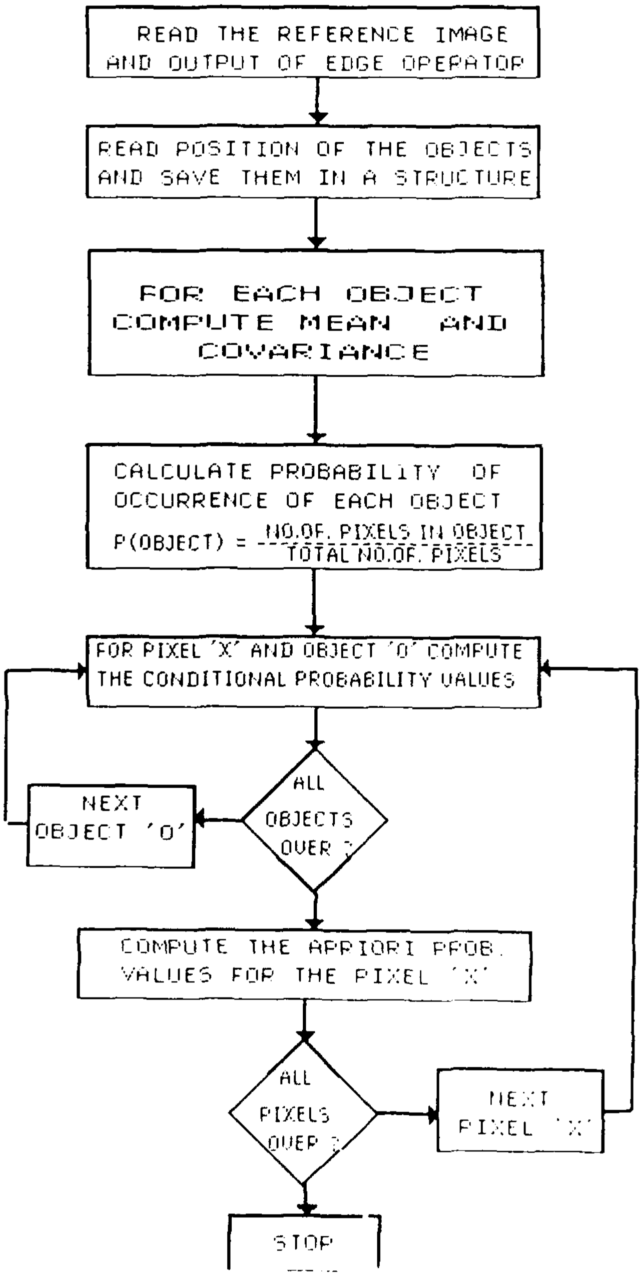
READ THE REFERENCE IMAGE AND OUTPUT OF EDGE OPERATOR
READ POSITION OF THE OBJECTS AND SAVE THEM IN A STRUCTURE
FOR EACH OBJECT COMPUTE MEAN AND COVARIANCE
CALCULATE PROBABILITY OF OCCURRENCE OF EACH OBJECT
P(OBJECT) = NO.OF. PIXELS IN OBJECT / TOTAL NO.OF. PIXELS
FOR PIXEL 'X' AND OBJECT 'O' COMPUTE THE CONDITIONAL PROBABILITY VALUES
ALL OBJECTS OVER ?
NEXT OBJECT 'O'
COMPUTE THE APRIORI PROB. VALUES FOR THE PIXEL 'X'
ALL PIXELS OVER ?
NEXT PIXEL 'X'
STOP

fig.4 algorithm to find apriori probabilities

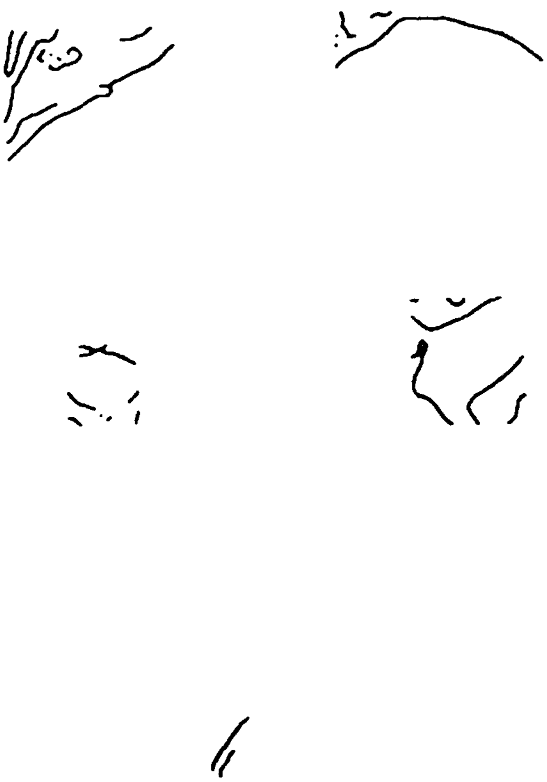

fig.3.2 - 3.6 individual features labeled

NORTH WALL (I) OF GULF STREAM

851.9	-51.9	-106.3	-10.3
-51.9	35.5	9.4	6.9
-106.4	9.4	55.2	-10.3
-10.3	6.9	-10.3	3000.4

NORTH WALL (II) OF GULF STREAM

891.0	3.6	-48.2	56.5
3.6	17.6	-19.2	6.9
-48.2	-19.2	119.3	-100.9
56.5	12.7	-100.9	3280.3

SOUTH WALL OF GULF STREAM

1349.5	78.4	-74.4	-318.4
78.4	4.8	-2.5	-22.3
-74.5	-2.5	44.7	-39.5
-318.4	-22.3	-39.5	3419.7

WARM EDDY (I)

143.8	-8.2	104.4	-128.8
-8.2	3.4	-9.2	15.9
104.4	-9.2	509.6	-203.5
-128.8	15.9	-203.5	3872.9

WARM EDDY (II)

228.5	-9.9	-17.1	58.6
-9.9	1.9	3.4	4.4
-17.1	3.4	23.7	33.1
58.6	4.4	33.1	3305.2

fig.5 covariance matrices