

AUTOMATIC EDDY EXTRACTION FROM SST IMAGERY USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT:

Mesoscale eddies have a significant impact on the exchange of material and energy in the ocean, and thus their knowledge are of great importance for the study of oceanic circulation. Images of sea surface temperature (SST) created from satellite infrared sensors are used to detect mesoscale eddies that have a surface signature in temperature. Various techniques, including texture analysis, wavelet transform, mathematical morphology, etc., have been used to identify mesoscale eddies from SST images. However, mainly due to the strong morphological variation of eddies which causes the absence of a valid analytical model, these approaches either have many limitations or are rather complex. The paper proposes a new methodology for automatic detection of mesoscale eddies from SST images using artificial neural network (ANN) and edge detection, and it can be summarized in the following steps: 1) pre-processing to reduce noise and to obtain maps of temperature gradient, its direction and magnitude; 2) using artificial neural network to detect the possible eddy centres; 3) removing the false eddy centres; 4) detecting the edge points of the eddies and fitting them into ellipses. This approach has been applied to the detection and extraction of mesoscale eddies in the Gulf Stream area using NOAA GOES 10 & 12 SST images, and the experiment has proved that this method has the following advantages: 1) It's effective and robust with high detection accuracy (over 90%), especially for the cold-core eddy (over 95%) since the training set used for the neural network is mainly composed of cold-core eddies. If more samples of eddies and non-eddies are used to train the neural network, the detection accuracy can be further improved. 2) Not only are eddies detected by the approach, but also the parameters of eddies such as centre location, size and direction are also calculated at the same time, which can be rather useful for detecting the change of eddies in sequential SST images. 3) The procedure is rather simple, efficient and easily reconfigurable, without the need of a valid analytical model. It can be adapted to different conditions such as different sizes of eddies, different cores (cold or warm), and different resolution of SST images. Therefore, the proposed approach is rather suitable for automatically detecting and extracting eddies from satellite SST images.

1. INTRODUCTION

Mesoscale oceanographic phenomena such as mesoscale eddies, fronts and upwellings have a significant impact on the exchange of material and energy in the ocean, and thus their knowledge are of great importance for the study of oceanic circulation. Compared to ordinary methods of in-situ observation, the technology of marine remote sensing has advantages in synoptic coverage of large areas of instant oceanic information, collection of long sequence data of global oceans, and measurement of marine features. Thus, it has become an important method of marine environment monitoring. The remote sensing imagery, through data processing and inversion, can provide lots of marine feature information related to mesoscale oceanographic phenomena, including sea surface temperature (SST), chlorophyll concentration, sea surface wind speed field, etc. Among them, SST, the first marine environment parameter obtained by marine remote sensing, is widely used in the research on mesoscale oceanographic phenomena, ocean-atmosphere heat exchange, global climate change, fishery resources and pollution monitoring (Feng, 1999). Since almost all the marine dynamic processes are related to SST directly or indirectly, mesoscale oceanographic phenomena such as mesoscale eddies, fronts, and upwellings can be effectively detected by using SST. With the massive increase of SST data, it is necessary and urgent to detect the marine phenomena in SST images automatically.

Various techniques, including texture analysis, wavelet transform, mathematical morphology, etc., have been used to identify mesoscale eddies from SST images. For instance, Alexanin and Alexanina (2000) described the SST images as a set of oriented textures in the temperature field, calculated the dominant orientation of the radiation contrasts and fitted it into the elliptical model of eddies. However, mainly due to the strong morphological variation of eddies which causes the absence of a valid analytical model, these approaches either have many limitations or are rather complex (Marcello, J. et al., 2004).

This paper proposes a new methodology for automatic detection of mesoscale eddies from SST images using artificial neural network (ANN) and edge detection.

2. APPROACH

The approach can be summarized in the following steps: 1) pre-processing to reduce noise and to obtain maps of temperature gradient, its direction and magnitude; 2) using artificial neural network to detect the possible eddy centres; 3) removing the false eddy centres; 4) detecting the edge points of the eddies and fitting them into ellipses.

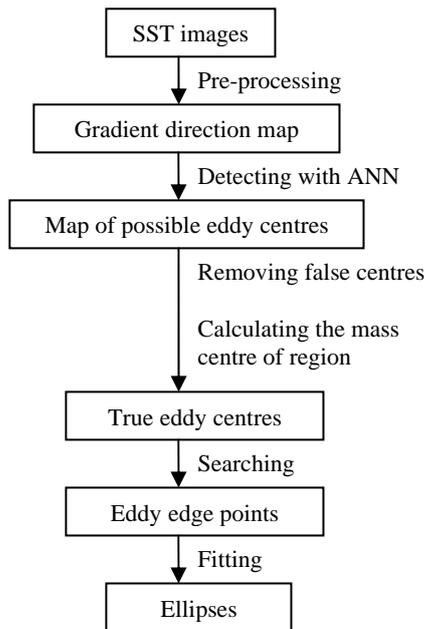


Figure 1. Eddy detection procedure

2.1 Pre-processing

In the first step, a low pass filter is used to reduce the noise caused by clouds and other atmospheric phenomena. Then, an edge detector such as Prewitt is applied to the filtered SST image to calculate the vertical and horizontal temperature gradients.

After the vertical and horizontal temperature gradient maps are smoothed by a local average operator, which can both reduce the noise and enhance areas of the strong gradient, map of the temperature gradient direction and magnitude is also calculated.

2.2 Detecting Eddy Centres with ANN

In the second step, for each point in the gradient direction map, a numerical vector describing the region surrounding the point can be obtained by using a binary mask centred on it and reading the gradient direction at '1' locations (Castellani, 2006). As shown in Figure 2, in which black represents '1' and white represents '0', a 9×9 mask is used to obtain a 81-dimensional vector representing the gradient field around the centre point.

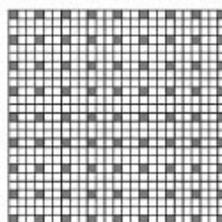


Figure 2. 9×9 mask

Hundreds of eddy centres and non-eddy centres in the SST images are selected by experts, and their corresponding numerical vectors of gradient direction are used as input to train the artificial neural network such as multilayer perceptron

(MLP) and self-organizing maps (SOM). And the output of the neural network is represented as a vector with two elements indicating whether it's an eddy centre or not.

Different structures and different parameters of the neural network are tested and assessed by the learning accuracy to achieve optimization. After the architecture is optimized and the neural network is trained, it can be used to scan the new gradient direction map calculated from a new SST image, and the result can also be a map in which each point is a positive or negative eddy centre response. For convenience, the grey level value of the point in the result map is assigned 255 when the response is positive and 0 when negative. Then, a map of possible eddy centres is obtained.

2.3 Removing False Centres

In the third step, the result map of possible eddy centres is smoothed by a local average operator to remove the noise, since the positive response should accumulate in the central areas of eddies while the false detections tend to be scattered evenly in the map. After the smoothing, an iterative threshold algorithm can be used to further remove false detections. In addition, the area of each connected region of possible eddy centres is calculated, and the region whose area is smaller than a certain threshold is removed.

2.4 Ellipse Fitting

In the final step, the centre of mass of each connected region in the detection result map is calculated and considered as the true eddy centre. In the corresponding gradient magnitude map, from each eddy centre, draw a line with a certain length every $\pi/256$ from 0 to 2π clockwise. The length of the line can be determined by the possible maximum radius of eddies in the area. For each point on the line, a mask is used to calculate the local average in its neighbourhood, and the result is assigned to this point.

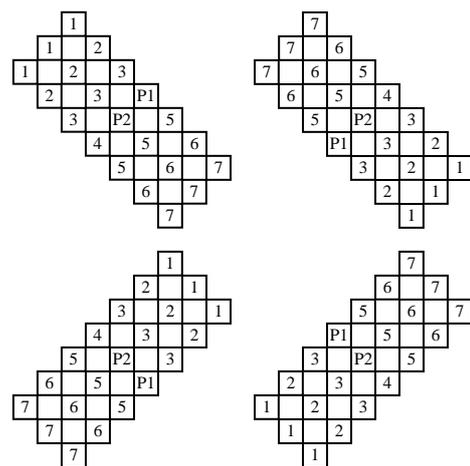


Figure 3. 3×7 oblique mask

As shown in Figure 3, P_1 is the current point on the line, and P_2 is the next point. The average gradient magnitude of the points with the same number is calculated, and the average of 7 average gradient magnitudes is assigned to P_1 .

Then, for each line, the location with the maximum value is found and considered as the edge point of the eddy. Therefore, a total of 512 edge points can be obtained for each eddy centre. Finally, according to the least squares principle, these edge points are fitted into an ellipse which can represent the location, size and direction of the eddy.

3. EXPERIMENT

This approach has been applied to the detection and extraction of mesoscale eddies in the Gulf Stream area using NOAA GOES 10 & 12 SST images.

3.1 Data

NOAA GOES 10 & 12 SST data is available from May 5 of 2003 to the present at a 6km spatial resolution, and its coverage is from 180W to 30W and 45S to 60N. Data is obtained at a near real-time rate with 1 hour, 3 hour, and 24 hour files of SST, and the data format is binary. Daily files of SST are selected for this experiment and read into ENVI using IDL procedure. Then, the SST images are cut into the size of 700×700 for the Gulf Stream area where eddy phenomena occur frequently.

43 SST images from 2003 to 2006 are used, and their gradient direction and magnitude maps are obtained. Then, 95 eddies are sampled, while 398 non-eddies are sampled. In the purpose of balance, eddy samples are duplicated to reach 380. Thus, a total of 778 vectors are obtained for the training of ANN. The whole data are divided into the training set (60%), the validation set (20%), and the test set (20%). The target is set as two-dimensional vectors: (1, 0) represents eddy and (0, 1) represents non-eddy.

3.2 Architecture and Parameters of ANN

This experiment chooses MLP (Lippmann, 1987), which is the multilayer feedforward network usually using backpropagation (BP) (Rumelhart et al., 1986) as the learning rule. It is composed of three parts: an input layer, one or more hidden layers, and an output layer. The input layer receives the input; the hidden layer receives the signals from the previous layer, sums them with weights, and uses transfer function to produce new signals; the output layer receives the signal from the hidden layer, and produces the output. BP algorithm consists of two processes: the feedforward of signals and the backpropagation of errors. If the output doesn't meet the requirement, errors will be propagated backward and apportioned to neurons and the weights and bias will be adjusted. These two processes repeat until the output meets the requirement or certain learning iterations are reached. Parameters such as learning rate and momentum constant can affect the speed of convergence and the performance.

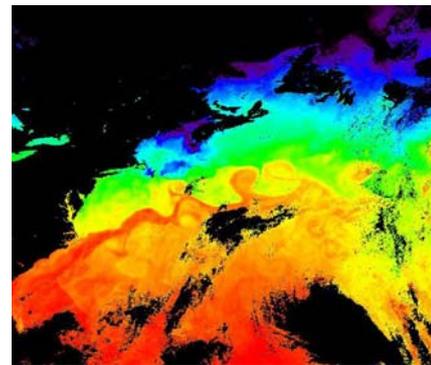
Different number of hidden layers, learning rate, momentum constant, and other different parameters are tested, and several architecture and parameters with good performance are shown in the Table 1.

| Hidden layer 1 | Hidden layer 2 | Learning rate | Momentum constant | Learning iterations | MSE | Non-eddy accuracy | Eddy accuracy | Total accuracy |
|----------------|----------------|---------------|-------------------|---------------------|-----------|-------------------|---------------|----------------|
| 10 | | 0.02 | 0.1 | 3000 | 0.0172192 | 0.9091 | 0.9857 | 0.9456 |
| 10 | | 0.04 | 0.3 | 3000 | 0.0281892 | 0.9351 | 0.9286 | 0.9320 |
| 5 | 3 | 0.03 | 0.2 | 1462 | 0.0257067 | 0.9103 | 0.9853 | 0.9452 |

Table 1. MLP training result

3.3 Scanning and Fitting

A new SST image (Figure 4(a)) is pointwise scanned using the trained network, and a map of possible eddy centres (Figure 4(b)) is obtained. Then, the map is smoothed by a 5×5 average mask (Figure 4(c)), and turned into binary map by thresholding method (Figure 4(d)). The area of each connected region in the binary map is calculated, and the region whose area is smaller than a certain threshold is removed. The mass centres of the remaining region are considered as true eddy centres. Finally, rays are drawn to detect the edge points, and the detected edge points are fitted into ellipses (Figure 4(e)).



(a) SST image on Day 247, 2005



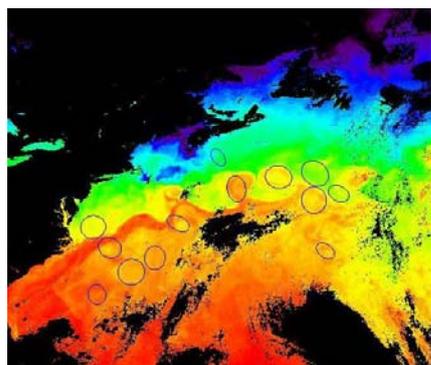
(b) Possible eddy centres



(c) Smoothed



(d) Binaryzation



(e) Fitted ellipses

Figure 4. Scanning a new SST image and fitting

3.4 Analysis

As shown in Figure 4, most of eddies in the SST image are detected and fitted well. A cold eddy is not detected, for it is very close to an area without temperature values. Two regions are falsely detected as eddies, for the characteristics of their gradient field are similar to those of eddy gradient field in some aspects. In order to overcome these problems, more samples of different kinds of eddies and non-eddies are needed to train the artificial neural network better. Other kinds of architecture and parameters of ANN are also needed to be tested.

4. CONCLUSION

The experiment has proved that this method has the following advantages. Firstly, it's effective and robust with high detection accuracy (over 90%), especially for the cold-core eddy (over 95%) since the training set used for the neural network is mainly composed of cold-core eddies. If more samples of eddies and non-eddies are used to train the neural network, the detection accuracy can be further improved. Secondly, not only are eddies detected by the approach, but also the parameters of eddies such as centre location, size and direction are also calculated at the same time, which can be rather useful for detecting the change of eddies in sequential SST images. Thirdly, the procedure is rather simple, efficient and easily reconfigurable, without the need of a valid analytical model. It can be adapted to different conditions such as different sizes of eddies, different cores (cold or warm), and different resolution of SST images. Therefore, the proposed approach is rather suitable for automatically detecting and extracting eddies from satellite SST images.

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