Efficient Algorithm for Feature Extraction from Oceanographic Images *

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Abstract

This paper presents a new computational scheme based on multiresolution decomposition for extracting the features of interest from the oceanographic images by suppressing the noise. The multiresolution analysis from the median presented by Starck-Murtagh-Bijaoui [4][5] is used for the noise suppression.

A parallel approach is presented for this computationally intensive problem of infrared images.

Keywords: Edge detection, multiresolution, wavelet transform, feature extraction, image processing, noise suppression.

1 INTRODUCTION

Exploiting of concurrency is a central and important problem in many computational intensive applications. One such application is the extraction of features for oceanographic images. Oceanographers require accurate methods of tracking features in satellite images of the ocean in order to observe and quantify surface layer dynamics. Infrared (IR) images of the ocean that depict the sea surface temperatures are widely used for such studies. The task of automatic feature tracking from time series of satellite IR images mainly poses the two problems. First, the features of interest have weak edges and constantly evolving shapes from image to image. Features merge, split, grow, shrink, disappear, or are created on time scales that are comparable to the sampling interval of the satellite imager (typically 12 hours). In other words, the phenomenology under investigation is turbulent fluid flow, not rigid body motion. Therefore, the tracking of ocean features presents a very difficult problem. The second problem, which results from the first one, is that the feature "motion" cannot be defined by a single set of values representing translation, rotation and scaling. Different motions occur at different spatial scales. Thus the motion must be defined by parameters that are functions of scale as well as space and time. A simple example of different motions associated with different scales is seen in the ocean "front". Most ocean fronts exhibit shear across the frontal boundary. Shear results in small lobes (shear instabilities) on the front which moves along the frontal boundary. Concurrently, the entire frontal feature may be moving perpendicular to the boundary direction. This scenario results in small scale and large scale motions that are orthogonal. A feature tracking algorithm based on the solution of rigid body problems will lead a result that represents some unknown mixture of these two orthogonal motions. Clearly, an efficient algorithm to resolve these two orthogonal motions is required. This is one aspect of the problem where concurrency can be exploited.

The wavelets have proven to provide an efficient technique for studying dynamic images. The wavelet transform, because it is able to localize signal in both space and frequency, maybe useful for addressing the problem of feature tracking in oceanographic images [7]. This paper deals with the problem of wavelet-based feature extraction. This is the first step in a feature tracking problem. We expore a parallel com-

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putational technique to this problem defined in our earlier paper on feature detection problem [6].

An important feature of the wavelet transform is the facility of characterization of the local regularity of a function, with important applications to texture discrimination in images. The wavelet transform can be generalized to any number of dimensions, but for the purpose of image processing only the two-dimensional case suffices. The wavelet transforms are able to capture the features of images at all resolutions. Thus, there is no limitation on the fineness of the recoverable image. This gives rise to a very important method of observing at and analyzing an image in terms of successive levels of resolutions.

Multiresolution decomposition involves decomposition of an image in frequency channels of constant bandwidth on a logarithmic scale. Multiresolution transforms have been the focus of extensive study soon after the work on multiscale edge detection by Rosenfeld and Thurston[3]. The details of an image characterize different types of physical features at different scales. While at a coarse resolution, one can distinguish the gross shapes of the large objects in an image. For a detailed analysis see [6].

2 The Discrete Wavelet Transform

Mallet's wavelet transform

A discrete wavelet transform approach can be obtained from multiresolution analysis (Mallet 1989). A multiresolution analysis is a set of closed, nested subspaces generated by interpolations at different scales. A function $f(x)$ is projected at each step j onto the subset V_j. This projection is defined by the scalar product $c_j(k)$ of $f(x)$ with the scaling function $\phi(x)$ which is dilated and translated by

$$c_j(k) = \langle f(x), 2^{-j}\phi(2^{-j}x - k)\rangle. \quad (1)$$

$\phi(x)$ is a scaling function which has the property:

$$\frac{1}{2}\phi(\frac{x}{2}) = \sum_n h(n)\phi(x-n). \quad (2)$$

Equation (2) permits the set $c_{j+1}(k)$ to be computed directly from $c_j(k)$. If we start from the set $c_0(k)$ we compute all the sets $c_j(k)$ with $j\rangle 0$, without directly computing any other scalar product. That is,

$$c_{j+1}(k) = \sum_n h(n-2k)c_j(n). \quad (3)$$

At each step, the number of scalar products is divided by 2. At each step, the signal is smoothed and the information is lost. The remaining information can be restored using the complementary subspace W_{j+1} of V_{j+1} in V_j. The subspace can be generated by a suitable wavelet function $\psi(x)$ with translation and dilation,

$$\frac{1}{2}\psi(\frac{x}{2}) = \sum_n g(n)\phi(x-n). \quad (4)$$

We compute the scalar products $\langle f(x), 2^{-(j+1)}\psi(2^{-(j+1)}x - k)\rangle$ as

$$w_{j+1}(k) = \sum_n g(n-2k)c_j(n). \quad (5)$$

In order to restore the original data, Mallet used the properties of orthogonal wavelets. But, the theory has been generalized to a larger class of filters (Cohen-Daubechies-Feauveau, 1992). Two other filters $\tilde{h}$ and $\tilde{g}$, the conjugates of h and g, respectively, have been introduced (Daubechies, 1992) and the restoration is performed using

$$c_j(k) = 2\sum_l [c_{j+1}(l)\tilde{h}(k+2l) + w_{j+1}(l)\tilde{g}(k+2l)]. \quad (6)$$

This analysis can be easily extended to the case of two dimensions. However, the two-dimensional algorithm is based on separable values leading to x and y directions being prioritized. This will lead to a non-isotropic analysis of the images which is not an efficient way to extract fine features in the oceanographic images.

3 Starck-Murtagh-Bijaoui wavelet transform [6]

We present some of our earlier results [6]. The problems mentioned earlier led to the development of other multiresolution tools. Starck-Murtagh-Bijaoui[4][5] modified the "a trous algorithm" and developed a new multiresolution approach using morphological median filter. The algorithm is as follows:

begin {

1. Define a mask M_t with a size t.

2. Initialize j to 0, and start from data c_0.

3. *med* being the filtering median function, compute $c_{j+1} = med(M_t, f_j)$ and median coefficients at

scale j by $w_{j+1} = c_j - c_{j+1}$

4. If j is less than the desired number of scales, return to 3.

} end

The reconstruction is carried out by a simple addition of all scales:

$$c_0 = c_p + \sum_j w_j. \tag{7}$$

We use the above algorithm to analyze and suppress the noise in the image at various scales.

A simple edge-detection algorithm [6]
Edge detection is an operation of locating the transition between two regions of distinct gray level properties. In the oceanographic images a region that appears to have a single gray level may actually contain several adjacent gray levels. That appear to be the same is the visual quantization of the observer. Based on this observation we present the following simple edge detection algorithm:

begin {

1. Scan the image with a 3×3 empty window.

2. On each move of the window compute the G_{max}, the maximum value in the window, and G_{min}, the minimum value in the window.

3. If $G_{max} - G_{min}$ is less than the threshold T, replace the central pixel with zero. Else move the window.

4. The set of all remaining points, E_j is the edge detected image.

} end

The selection of the threshold in the third step is the most sensitive part of this algorithm. The choice of the threshold (usually a number between 0 and 255) depends on the image. Since the changes in intensity occur at different scales in an image, their optimal detection requires the use of operators of different thresholds. If the difference between the intensities of the regions in the image is small, a smaller threshold is required. And if the difference is large, a higher threshold can be used.

We can define a multiresolution approach for edge detection at different scales. A multiresolution analysis is defined as a closed nested set of subspaces. Let E_j be the set of edges in an image at the resolution j, such that

$$E_j = edge(I_m, T_j) \tag{8}$$

where I_m is the original image, T_j is the threshold and *edge* is the set of edges obtained using the above algorithm.

As we increase the resolution (to a finer resolution) to $j = j - 1$ and $T = T - t$ where t is a small number, the number of edges detected will increase as more and more fine edges can be detected. As we decrease the resolution the number of edges detected will decrease. The information that is lost as we move to a coarser resolution can be restored using the complementary subspace W_{j+1} of V_{j+1} in V_j using

$$W_{j+1} = E_j - E_{j+1}. \tag{9}$$

This implies that the set of edges forms a sequence of nested subspaces satisfying the following two conditions:

$$\ldots \subset E_{-1} \subset E_0 \subset E_1 \subset \ldots$$

$$\bigcap_{n \in Z} V_n = \{0\}$$

The reconstruction of the edges is then carried out by a simple addition of all the scales

$$E_f = E_c + \sum_j W_j \tag{10}$$

where E_f is the set of edges at the "finest" scale and E_c is the set of edges at the "coarsest" scale.

4 Computational scheme for feature extraction

In order to address the problem of feature tracking, it is important that the features have well-defined edges with the contour information well preserved. We present the following scheme defined in [6] to extract well defined features from oceanographic images. This scheme incorporates parallelism by distributing the input pixels across a series of processors. This will lead to the efficient computation of transforms and extraction of features.

Step 1. Generation of set of wavelet plane in parallel. Apply Starck-Murtagh-Bijaoui wavelet transform to the input image in parallel and generate a wavelet plane. Then, Starck-Murtagh-Bijaoui will be applied to the input images which are distributed across a number of processors. This will generate a set of wavelet planes.

Step 2. Supress coefficient below a certain value in parallel. Make all the insignificant wavelet coefficients, that is all the coefficients below a user specified value zero. This threshold will often depend on the application. This will be done in parallel of each wavelet plane.

Step 3. Reconstruct the edge image with the remaining coefficients in parallel. This consists of two steps. First, image reconstruction is done for each wavelet plane in parallel. Then the images corresponding to different wavelet planes will be unified using a parallel union algorithm. The resulting reconstructed image will be stored in one of the processors.

Step 4. Choose a threshold and apply the edge detection algorithm described in the previous section.

Step 5. If the edges are not satisfactory, $j = j + 1$, decrement the threshold and goto Step 4.

Such a scheme has several advantages:

(1) The transform can be carried out with integer values only, and in parallel.

(2) Structure contours are preserved.

(3) The algorithm can be easily modified to work on intermediate scales (other than dyadic). See figure 1.

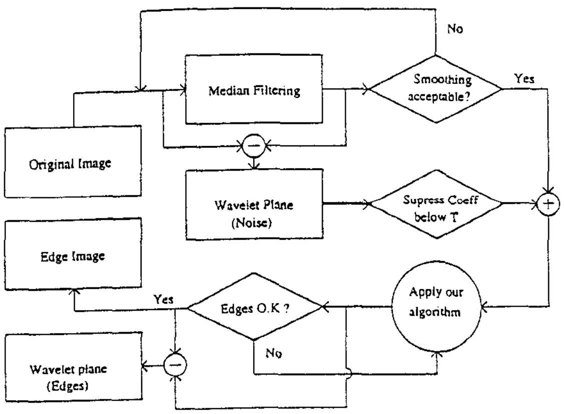
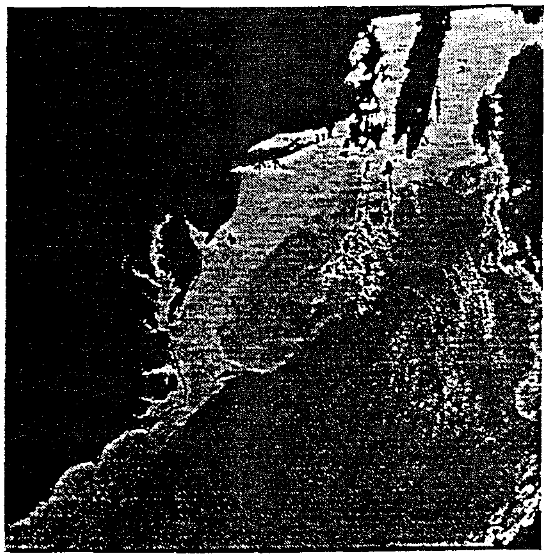


Figure 1: Computational Architecture

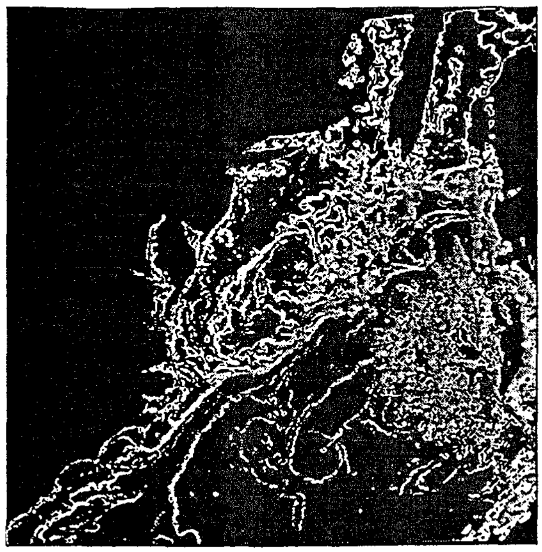
5 Experimental results [6]

The following figures 2(a,b,c,d) show a characterization of features obtained using methods described in [6].

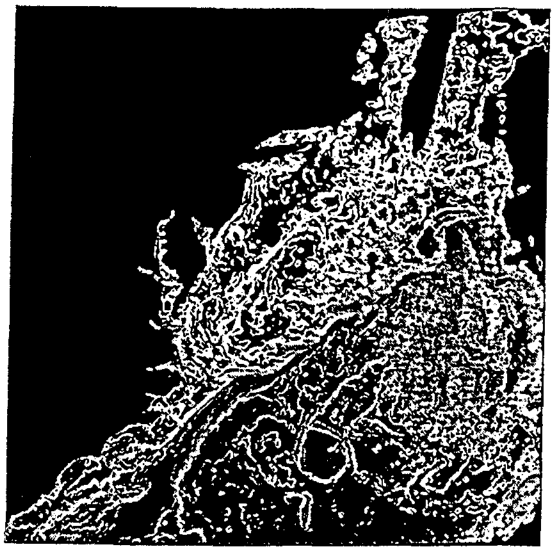
Figure 2.



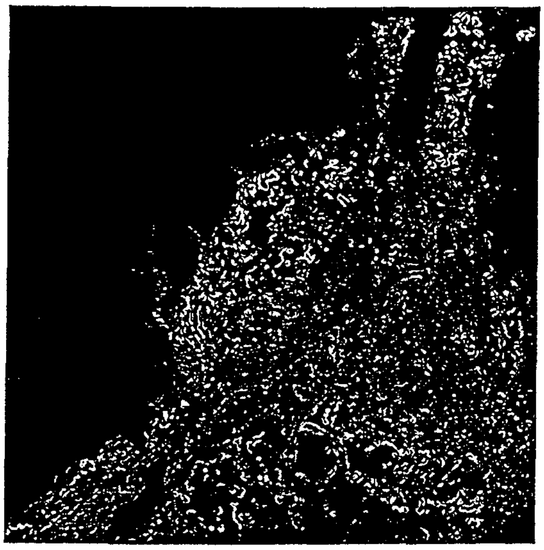
(a) Original image



(b) Edge image E_j at $T = 2$



(c) Edge image E_{j+1} at $T = 3$



(d) Complementary image W_j

All these images have weak edges and a significant amount of noise.

5.1 Comparision with conventional detectors [6]

In this section we compare our method for detecting edges with the the most frequently used conventional edge detectors such as the Sobel edge operator and the morphological edge detector. For details see [6].

Sobel operator
The Sobel edge operator consists of two convolution kernels as shown in the following figure 3(a,b,c). The kernel shown in (a) is sensitive to horizontal edges while (b) is sensitive to vertical edges.

The output of the Sobel edge operators to a typical satellite image is shown in the following figure, show the output of S_h and S_v respectively. Notice the weakness of the response to the Sobel operator to the edges of the gulf stream and other eddies.

Morphological operator
Another approach to edge detection involves a nonlinear method based on morphological filtering of an image. Morphologic operators can be visualized as working with two images, the original image and the structuring element. The *dilation* of a binary image f by a structuring element S is defined as

$$f \oplus S = \{a + b | a \in f \wedge b \in S\} \tag{11}$$

The *erosion* of a binary image f by S is defined as

$$f \ominus S = \{a - b | a \in f \wedge b \in S\} \tag{12}$$

The *"dilation"* d of a gray-scale image f by a structuring element S is defined as

$$d(i,j) = MAX(f(i+x, j+y) \oplus S(x,y)), \tag{13}$$

where x and y are the coordinates of a cell in S whose center cell is the origin, and $(i+x, j+y)$ is in the domain of f. Similarly, "erosion" of a gray-scale image f by a structuring element S is defined as

$$e(i,j) = MIN(f(i+x, j+y) \ominus S(x,y)). \tag{14}$$

The morphological gradient of an image, say G, is given by

$$G = d(i,j) - e(i,j). \tag{15}$$

Figure 3.

Grayscale Threshold Value = 64

(a) Sobel Gradient

(b) Morphological Gradient

(c) Our Method

6 Conclusions and future work

This paper presents a methodology to exploit parallelism is an algorithm developed in [6]. The emphasis is on deriving a current value of the wavelet coefficient during the partitioning of wavelet planes.

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