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Performance Evaluation Of Some Algorithms For Acoustic Images Using Image Segmentation Techniqes

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Abstract

This paper is concerned with Unsupervised sonar image segmentation .We present a new estimation and segmentation procedure on images provided by a high resolution sonar. The sonar image is segmented in to two kinds of regions:Shadow (corresponding to a lack of acoustic reverberation behind each object lying on seabed) and Reverberation (Due the reflection of acoustic wave on the seabed and on the objects).The unsupervised contextual method is defined as a two-step processExpectation Maximization Algorithm and Statistical Region SnakeTheory[1]. The expectation maximization algorithm is very useful for parameter estimation problems in finite mixtures. The stochastic EM algorithm is a widely applicable approach for computing maximum likelihood estimates for the mixture problem[2].During past years the active contour models (Snakes) have been widely used for finding the contours of objects. This segmentation strategy is classically edge-based in the sense that the snake is driven to fit the maximum of an edge map of the scene.This technique has been successfully applied to real sonar images, and is compatible with an automatic processing of massive amounts of data.

IndexTerms: Active contours , Image edge detection , Imageprocessing ,Unsupervised Imagesegmentation ,Expectation,MaximizationAlgorithm, Snake Algorithm **,**

Introduction

In image analysis, image segmentationis the partition of a digital image into multiple regions (sets of pixels) with each region associated with one of a finite number of classes that are modeled as distinct random fields[3]. An important problem is that of parameter estimation since the random field models are mostly parametricmodels specified by a small number of parameters which have to be estimated from the data. In most of the previous considerations, supervised approacheswhich usually assume training data to be available for image classes, the parameters can be estimated from the training data before segmentation is widely used. Although this supervised approach avoids the complexity of a combined problem of estimation and segmentation, it is rather unrealistic in many practical situations.

To automatically detect objects in side-scan sonar images, supervised approaches are difficult due to the large variability in the appearance of side-scan images. Thus, unsupervised approacheswhich also allow analysis to be carried out while the data is being collected, enabling mission plans to be changed depending on the data collected are strongly needed[4].

In sonar imagery, three kinds of regions can be visualized: highlight, shadow, and sea bottom reverberation areas. The highlight information is caused by the reflection of the acoustic wave on the object, while the shadow zone corresponds to a lack of acoustic reverberation behind the object.

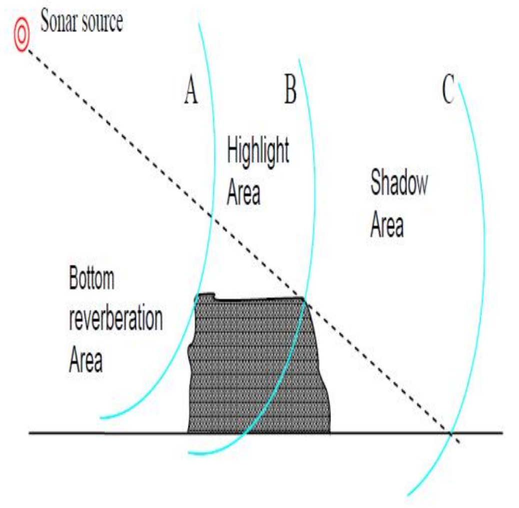
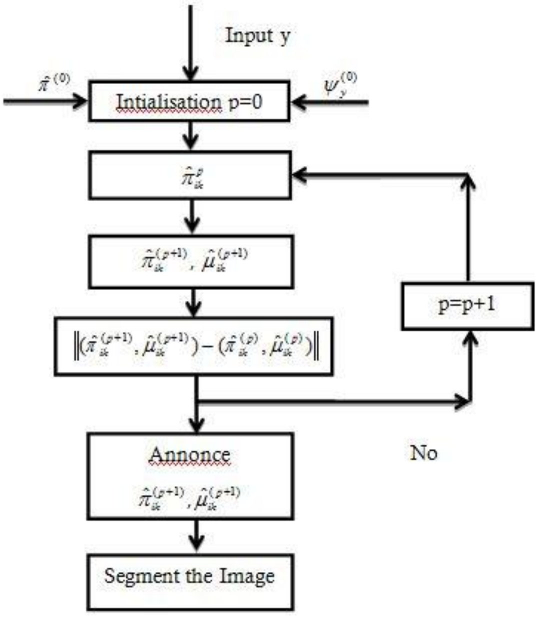


Fig (1) The formation of object area in side scan image

System Model& EM Algorithm



The EM algorithm is the most general effective algorithm for solving in complete data problems. The definitive reference for this algorithm was written by Dempster, Laird & Rubin in 1977. Basically it works as follows.

Let x= (y^T, z^T) be a set of random data of interest, where y is the observed data & z is the part of x that is not observable. For example, in image segmentation y is the set of image pixel intensities and is observable, whereas z is the image class status of the pixels that is not visible. Usually the observable y is called the incomplete data, & x is called the complete data.

Let g(x/Ψ) be the probability density function of the complete data, where Ψ is a parameter vector that characterize the density function. The incomplete data problem is to estimate Ψ based only on the observations represented by the incomplete data y.

It generates from some initial approximation Ψ(0), a sequence of estimate Ψ(p), where each iteration consist of the following two steps

Expectation-step(E=step)

Determine the function

$Q(\Psi|))=E[\log(g(X|\Psi))|y,(p)]$ (1)

Maximization-step(M-step)

Find the maximizor

$\Psi^{(p+1)\,)}=\arg\max^{(Q(\Psi|\,(p)))}$ (2)

Here, p represents the p^{th} iteration. It has been that under some relatively general conditions, the estimate converges to the ML estimate of the incomplete data problem, at least locally.

Model of EM Algorithm

This is the simplest case, where the data is fully categorized. The fully categorized data can be generally represented as $\{x_i,i=1,\ldots\ldots,N\}=\{(y_i,\mathbf{z}_i^T)^T,i=1,\ldots\ldots,N\}$(3)

Where each $\mathbf{z_i}=(z_{i,1},\ldots\ldots,z_{i,k})^T$ is an indicator vector of length k with 1 in the k^{th} position & zeros elsewhere. Then the likelihood function corresponding to ($\chi_{i,\ldots\ldots,}\ \chi_N$) can then be written in the form

$$g(X|\psi)=\prod_{i=1}^{N} f(\chi_i|\psi)=\prod_{i=1}^{N} f(y_i, z_{i1},\ldots, z_{ik}|\psi)$$

$$\hat{\pi}_k^{(p+1)} = \frac{1}{N}\sum_{i=1}^{N}\hat{\pi}_{ik}^{p} \quad ;k=1,2,\ldots K,$$

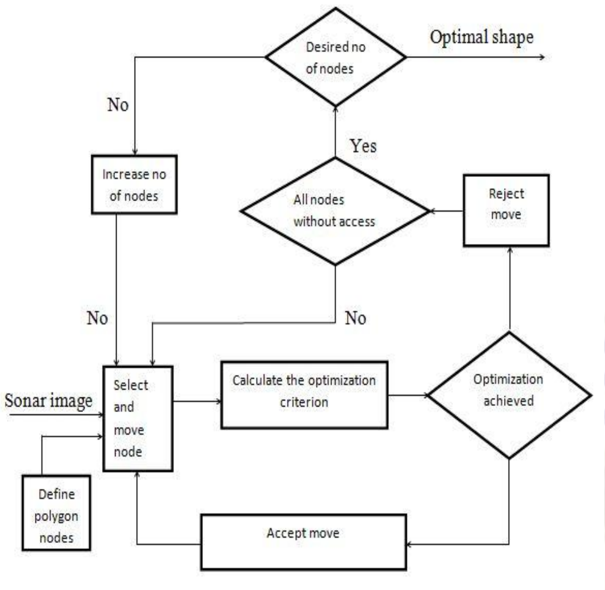
Snake Algorithm

The technique discussed in this section is based on research conducted in [1], where snakes are used under a statistical framework to segment images. Whilst many region based techniques are often computationally insensitive, the techniques described here is very fast, allowing much of the intensive calculations to be computed before the segmentation commences. This is possible when the statistical laws present in the image can be described by the exponential family, making the approach applicable in a wide range of physical situations[12].

Assume that the observed scene (The raw side scan sonar image) y is composed of two areas: Target (Shadow or highlight) and background of, we wish to, segment the target region. We consider the image y $=\{y(i,j)|(i,j)\in[1,N_i]\times[1,N_j]\}$ to be composed of $N_i \times N_j$ pixels where the gray levels of the N_t target pixels and the gray levels of N_b Background pixels are assumed to be uncorrelated and independently disturbed. They are described by their respectively probability density functions $f(y(i,j)|\theta_t)$ and $f(y(i,j)|\theta_b)$ where θ_t and θ_b Are the parameters of the probability density functions[10].

We define a binary window function $W=\{w(i,j)|w(i,j)\ \in[1,N_i]\ \times[1,N_j]\}$ which defines the shape of the snake at any instant of time. Defining w(i,j) to be equal to 1 inside the windowand 0 elsewhere, the image becomes composed of tworegions $\Omega_t=\{(i,j)|w(i,j)=1\}$ and $\Omega_b=\{(i,j)|w(i,j)=0\}$ so that the observed image can be viewed as the sum of two component

$y(i,j)=t(i,j)w(i,j)+b(i,j)(1-w(i,j))$ (4)



Where t(i,j) and b(i,j) are values drawn fromtheir respective probability distributions.

Therefore the purpose of segmentation becomes to estimate the most likely shape w for the target in the sense. Without any a priori knowledge about the shape of the target, the best w is chosen by maximizing the likelihood function[8].

g[y|w, θ_t, θ_b]=g($\chi_t | \theta_t). g(\chi_b | \theta_b$) (5)

The likelihood function is expressed as a product of probabilities as the pixels are assumed to be uncorrelated and

χ_u ={y(i,j)|(i,j)∈ Ω_u }(u=t or u=b). (6)

As we can see the likelihood function in (5.2) depends on the parameters of the probability functions as well as the window shape **w**. the parameter vector θ_u

where u∈{t,b} are the priori unknown and are in general of ni interest .However for segmentation to be possible it is necessary to compute these values. The parameters can be calculated using a variety of techniques such as a maximum a posteriori approach, but for simplicity, a maximum likelihood approach is again utilised as no a priori knowledge on the values of the parameters is available[8].

In order to proceed one has to specify parameters expression for the probability density functions f(y(i,j)| θ_t) and f(y(i,j)| θ_b Here we consider probability density functions which belong to the exponential families for r(i,j) and b(i,j). Taking into account the sufficient statistics if we choose Maximum likelihood estimation and insert these estimates in the likelihood function l(y,w)[9].

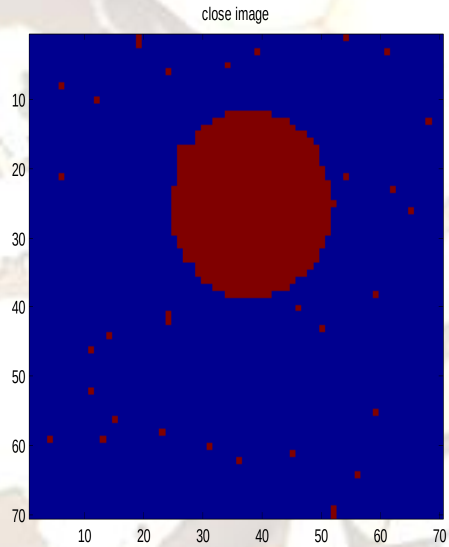
l(y,w)=log{ $G_t[t(\chi_t]$ }+log{ $G_b[t(\chi_b)]$ }(4)

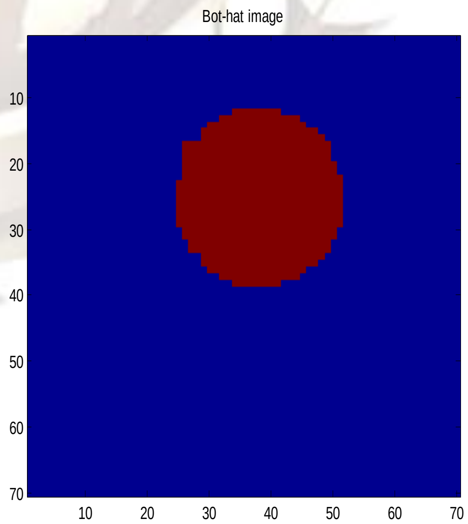
Where G_u are the functions which depend on y only via t(χ_u).

The window function w that maximizes the criterion J(y,w)=-l(y,w) then performs a maximum likelihood segmentation of the target in the sense. The criterion can consequently be regarded as energy acting on the snake since its minimization forces the contour to surround thetarget. For this purpose, we can use an iterativealgorithm in which we have to calculate the criterion J(y,w) for each deformation of the snake. Thus, the minimization procedure can be time consuming. In the next section, we show how to obtain the optimal criterion J(y,w).

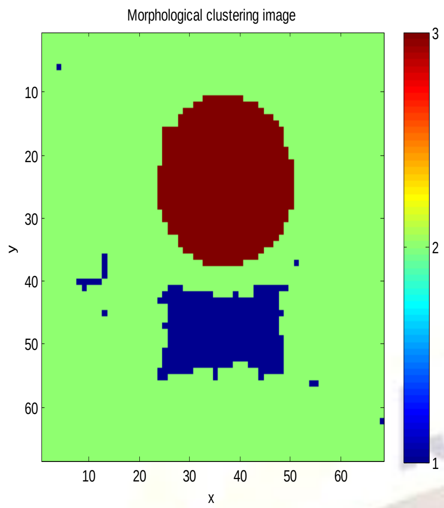
Simulation Results

Side scan sonar Images

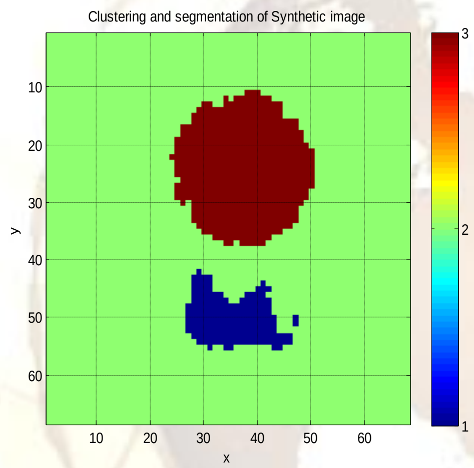


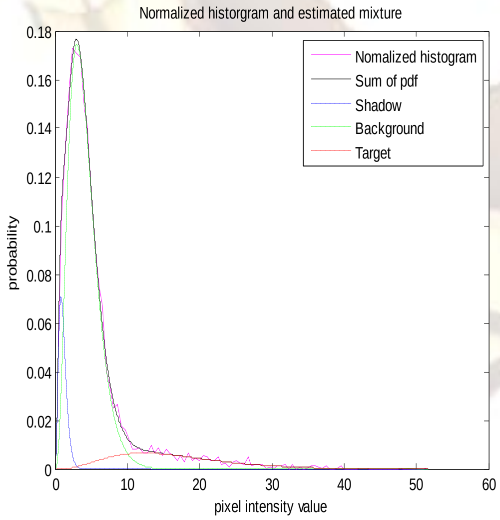


EM Algorithm



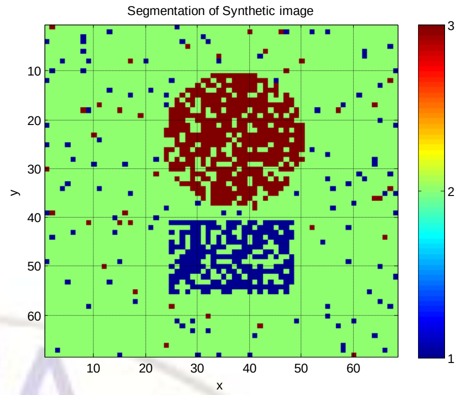
Probability Density of the Three Pixel Classes (Good Conditions)

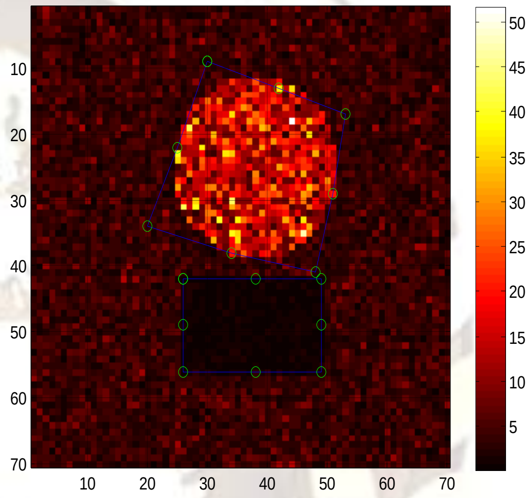




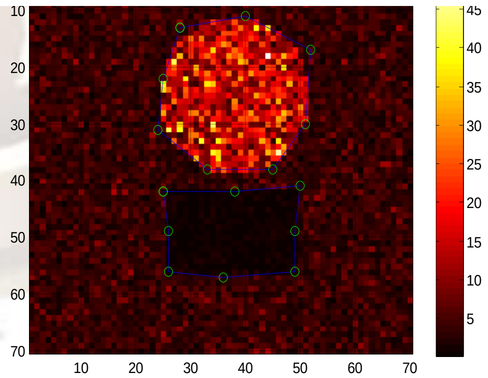
Snake Algorithm:

Segmentation result of a synthetic image





Iteration Result: Polygon 8 Nodes (Bad Highlight Contrast)



Iteration Result: Polygon 4 Nodes (Bad Highlight Contrast)

Conclusion

Image processing is a rapidly growing area of computer science. Its growth has been fueled by technological advances in digital

imaging, computer processors and mass storage devices. Fields which traditionally used analog imaging are now switching to digital systems, for their flexibility and affordability. Important examples are medicine, film and video production, photography, remote sensing, and security monitoring.
Nowadays, image segmentation represents a task of growing importance in many different fields. This technique is finding broad applications in underwater acoustics, space born remote sensing, medical imaging systems, non-distractive material analysis, as well as spoken language processing[14].

This paper concludes that it is to explore the potential growth areas of using these two algorithms in side scan imagery. Evaluating and comparing their performances for both synthetic and real sonar images using the software simulation tool MATLAB.

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