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Various Image Segmentation Method for Underwater Acoustic Image – A Survey

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***Abstract*— Image Segmentation is considered as one of the main technique in image processing. It divides an image into multiple regions in order to analyze them.Segmentation is very easy in generic images as the foreground object is easily differentiable with the background objects. The characteristics of underwater acoustic image are so different that it consists of texture with seafloor and sediments. The living and nonliving resources available in the seabed are not visible in the acoustic images.This paper is a survey of various image segmentation methods applied for underwater acoustic images.**

***Index Terms—Image Segmentation*, Acoustic Image.**

I.INTRODUCTION

Segmentation techniques bridge the gap between low-level technique and high-level image processingmethods. Segmentation techniques will be used in many applications such asobject detection, recognition, and measurement of objects in images[11].

Each segment which is obtained from segmentation process will represent some kind of information to user in the form of color, intensity, or texture. Hence, it is important to isolate the boundaries of any image in the form of its segments[11]. This process of segmentation will assign a single value to each pixel of an image in order to make it easy to differentiate between different regions of any image. This differentiation between different segments of image is done on the basis of three properties of image, i.e., color, intensity, and texture of that image. Therefore the selection of any image segmentation technique is done after observing the problem domain.

The importance of Image segmentation can't be neglected because it is used in almost every field of science, i.e., removing noise from an image, medical images, satellite imaging, machine vision, computer vision, biometrics, military, image Retrieval , extracting features and recognizing objects from the given image.

The classical segmentation-based clustering follows awell-known path that involves several processes includingpattern representation and its available number, and thescale of the features available to the clustering algorithm.Some of this information may not be controllable by thepractitioner. In addition to the feature selection, the mosteffective subset of the original features is identified for usein clustering.

II.IMAGE SEGMENTATION METHODS

All basic image segmentation techniques currently being used by the researchers will be discussed andevaluated in this section.

A.Otsu Segmentation

Otsu proposed the maximum classes variancemethod for image segmentation[1]. For its simplecalculation, stability and effectiveness, it has been widely used,is a well-behaved automatic threshold selection method, and itsconsumed time is significantly less than other thresholdingalgorithms.

Set the pixels of the segmenting image as N, there are$L$ gray levels (0,1,..., L -1) , and $n_i$pixels whose gray level is$i$,then$N = \sum_{i=0}^{L-1} n_i$, and we express the probability density distribution with the form of histogram
$p_i = \frac{n_i}{N}$, $\sum_{i=0}^{L-1} n_i = 1$, $p_i \geq 0$.

Assume the image is divided into two categories C_0 and$C_1$with threshold t , then C_0And C_1 respectively correspond to the pixels whose grey level are $\{0,1,\ldots,t\}$ and $\{t+1, t+2, \ldots, L-1\}$. Assume $\boldsymbol{\sigma}_B^2(t)$ isclasses variance when the threshold of the histogram is t then the optimal threshold could be obtained through solvingthe maximum of $\boldsymbol{\sigma}_B^2(t)$, that is

$$\boldsymbol{\sigma}_B^2(t^*) = \max_{0<t<L-1} \{\sigma_B^2(t)\}$$

The shortage of Otsu algorithm:

(1) In dealing with images discontinuous on grey level,with traditional Otsu algorithm the obtained threshold couldn'tfind a good convergence to the global optimum[2].

(2) Although the Otsu algorithm does not make anyassumptions on the probability density function, and expressthe two target and background probability density functions,only making use of the mean and variance, so it assume the twoprobability density functions could be expressed with the use ofthe two statistics,[3] however, it's not the case.

(3) When the global distributions ofthe target andback -ground vary widely, Otsu algorithm will fail.

(4) Otsu algorithm is suitable on condition that there aretwocategories in the image; When there are more than twocategories in the image, the method must be modified, so

as todecide multi-threshold. The approach allows the largestbetween-class variance and the smallest in-class variance

(5) With Otsu algorithm the image is divided into twocategories, even if the division makes no actual sense. In fact, the method couldn't be applied directly in case of variableillumination conditions[4].

Improved Otsu algorithm:

(1) Calculate the grey level $L$of the image .Calculate themean grey level value $\mu_T$of the image, and round off$\mu_T$to$[\mu_T]$ •as the grey level of the image, that is$L$ • •$[\mu_T]$ • •

(2) Assign initial value for segmentation time J =1 ;

(3) The implementation of Otsu algorithm. With Otsualgorithm calculate the pixel N, threshold K , thresholdselection function in-class variance σ_w ;

B.Adaptive k-mean segmentation

The adaptive K means clustering algorithm starts with the selection of K elements from the input data set. These K elements form the seeds of clusters and are randomly selected. The properties of each element also form the properties of the cluster that is constituted by the element. The algorithm is based on the ability to compute distance between a given element and cluster. This function is also applied to compute distance between two elements. An important consideration for this function is that it should be able to account for the distance based on properties that have been normalized so that the distance is not dominated by one property or some property is not ignored while distance computation [5]. In most cases, the Euclidean distance may be sufficient. For example, in the case of spectral data given by 'n' dimensions, the distance between two data elements E1 and E2, is equal to

$$\sqrt{(E_{11}-E_{12})^2+(E_{12}-E_{22})^2+(E_{1n}-E_{2n})^2}\ ,$$

Where E1= {E11, E12,…, E1n} and E2 = {E21, E22,...., E2n}

It should be noted that due to better performance, the square root function may be neglected. In other cases, there is need to modify the distance function. Such cases can be shown by data in which one dimension is scaled different compared to other dimensions or the properties may be required to have different weights during comparison [6]. With the distance function, the algorithm is as follows:

Compute the distance of each cluster from every other cluster and stored as a triangular matrix in a 2D array.[7] Minimum distance Dmin between any two clusters Cm1 and Cm2 and also identification of these two closest clusters is noted down.

For each non clustered element Ei, distance of Ei from every cluster is to be computed. For assignment of this element to a cluster, there may be following three cases:

1. If the distance element and the cluster is 0, assign the element to that cluster, and begin working with the next element.

2. If the distance between the element and cluster is less than the distance dmin, assign this element to its nearest cluster. As a result of this assignment, the cluster representation, or centroid, may change. The centroid is recomputed as an average of properties of all elements in the cluster[8]. In addition, the distance of the affected cluster from every other cluster, as well as the minimum distance between any two clusters and the two clusters that are closest to each other is recomputed.

3. When the distance Dmin is less than the distance of the element from the closest cluster, select the two closest clusters Cm1 and Cm2 ,and merge Cm2 into Cm1. Demolish the cluster Cm2 by removing all the elements from the cluster and by deleting its representation and add the new element into this empty cluster, successfully creating a new cluster. The distances between all clusters are recomputed and the two closest clusters identified over again.

C. Texture segmentation

In order to produce a texture gradient we first need tocharacterizethe texture content of the image at each pixel.[9]A numberof methods have been proposed to do this. One of themost populartechniques is the use of a set of scaled and orientated complexGabor filters By suitable spanning of the frequencyspace, each pixel can be characterized in texture content[10].However, when considering the differences in texture withinan image (e.g., the texture gradient) this often produces suboptimalcharacterization for segmentation.

To produce an optimalsystem, the Gabor filters need to be tuned to the texture contentof the image.Different schemes for adaptive Gabor filtering have been implemented . These and other schemes usearbitrary techniques that are entirely separate from the texturefeature extraction process whilst also being excessively computationallycomplex.

In order to integrate an adaptive scheme with the texture featureextraction process we have developed the Non-DecimatedComplex Wavelet Packet Transform (NDXWPT). The magnitudeof the coefficients of each complex subband can be usedtocharacterize the texture content.

This is because the basisfunctions from each subband (very closely) resemble Gabor filters,i.e., they are scale and directionally selective whilst being frequencyand spatially localized.Each pixel can therefore be assigned a feature vectoraccording to the magnitudes ofthe NDXWPT coefficients.A pixel at spatial position has one feature for eachNDXWPT subband coefficient magnitude at that position:defined as , where is the subband number.

A featurevector is therefore associated with each pixel characterising the texture content at that position.

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III.RESULTS

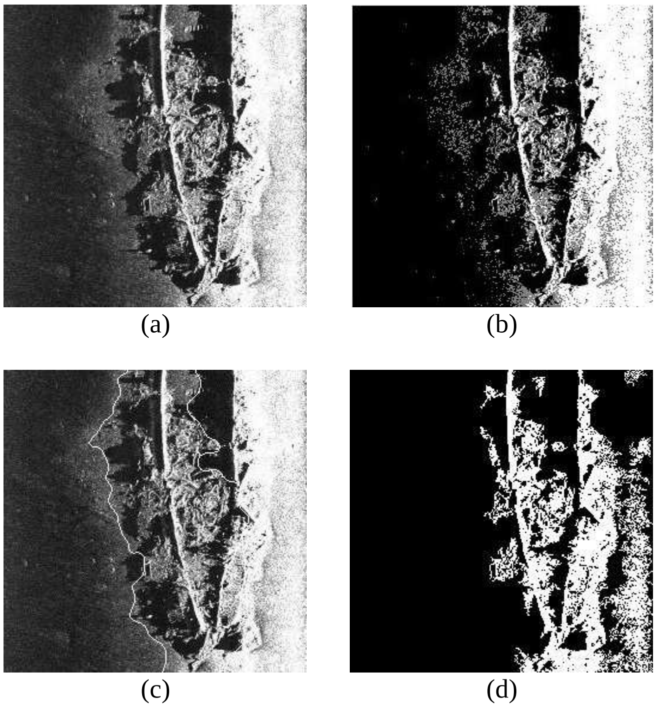

Fig. 1. (a) Input Image1 , (b) Adaptive k-mean , (c) Texture Segmentation , (d) Otsu Segmentation ,

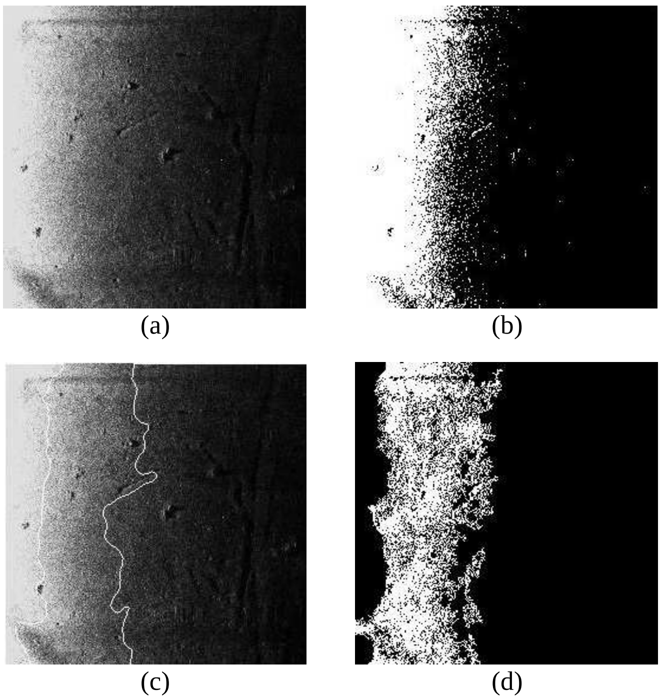

Fig. 2. (a) Input Image 2 , (b) Adaptive k-mean , (c) Texture Segmentation , (d) Otsu Segmentation .

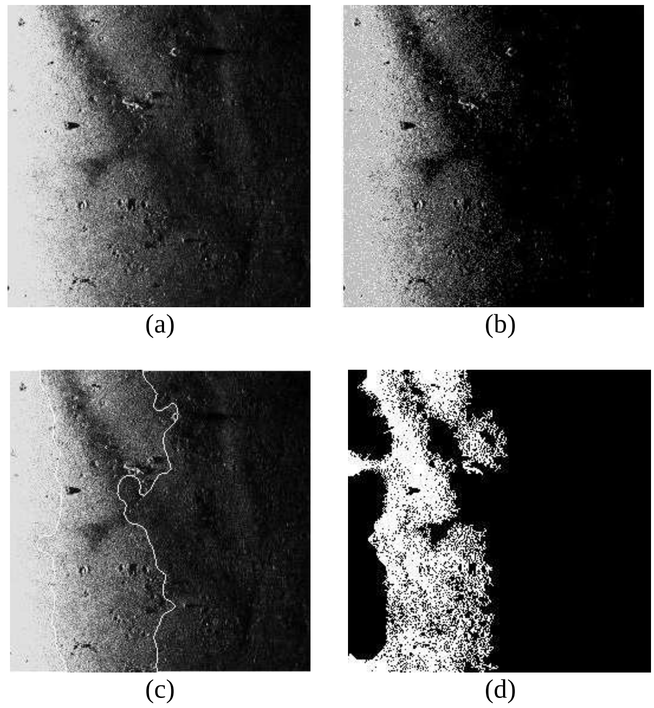

Fig. 3. (a) Input Image 3 , (b) Adaptive k-mean , (c) Texture Segmentation , (d) Otsu Segmentation .

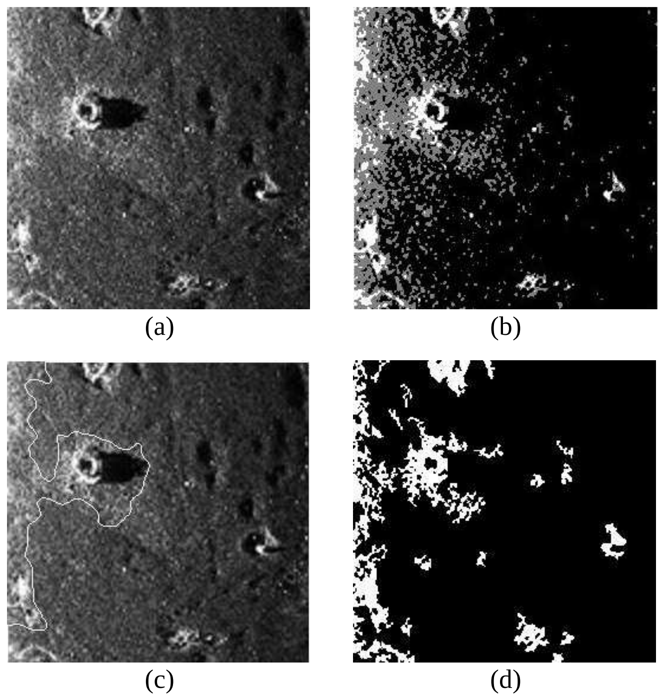

Fig. 4. (a) Input Image 4,(b) Adaptive k-mean , (c) Texture Segmentation , (d) Otsu Segmentation .

IV CONCLUSION

In this paper, various techniques of image segmentation has been discussed, an overview of all related image segmentation techniques has been presented in this work. After the analysis of different techniques of image segmentation, Adaptive k-mean, ostu methods are reasonably good thresholding methods if one demands more uniformity and better shape of the object in the binary image. Although number of techniques are available, each technique works on specific concept hence it is important which image segmentation techniques should be used as per application domain.

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