Stable Underwater Image Segmentation in High Quality via MRF model

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***Abstract---* The underwater image segmentation in high quality is one of the important parts in ocean investigations. Markov random field (MRF) based framework has been considered as one powerful statistical estimation approach for the spatial continuity on the basis of the Bayesian theory. However, in the underwater imaging system, poor visibility in the sea and the variations in the illumination, viewpoints, etc., have limited the application of the standard MRF and cause the sensitivity to the speckle noises in underwater image segmentation. Hereby, in this paper, we try to explore one kind of the underwater image segmentation scheme combining the MRF model and Hard C-means(HCM) clustering technique with the regional labeling and the local characteristics concerned, achieving great performances in both robustness and effectiveness.**

Keywords---underwater image segmentation; Markov random field (MRF); Hard C-Means; MRF-MAP

I. INTRODUCTION

Underwater image segmentation is the basis of underwater image for subsequent processing. It refers to the technique that partitions a digital underwater image into multiple segments and is typically used to identify regions of interest (Regions of Interest, ROI) or other relevant information in digital underwater images. Its purpose is to extract labeled regions for targeted objects for subsequent processing such as surface description and object recognition.

In the literature, a number of algorithms for segmentation of underwater images have been presented. e.g., thresholding methods [1], clustering methods [2, 3], edge-based methods [4], region splitting and merging methods [5, 6], and multi-resolution techniques [7]. Unfortunately, properties of the light in the water, such as the limited range, non-uniform lighting, low contrast, diminished colors, blur imaging and so on may limit the application of the classical image segmentation methods and cause the sensitivity to the speckle noises in underwater image segmentation [8, 9].

In this paper, we try to explore one kind of the underwater image segmentation scheme combining the MRF [10-14] model and HCM [2, 3, 15] technique with the regional labeling and the local characteristics concerned. The rest of the paper is organized as follows. Section II describes the basic framework of our approach. Section III presents the adaptive Hard C-means clustering algorithm and Section IV discusses inference of a simple MRF based segmentation model for feature space. Section V addresses how to implement the segmentation model. Experimental results obtained by the method on real scenes are reported in Section VI, along with comparisons to those obtained by other classical underwater image segmentation approaches. Conclusions are drawn in Section VII.

II. GENERAL FRAMEWORK

A brief flow chart of our proposed underwater image segmentation framework is shown in Fig.1. The steps are as follows: 1) The initial underwater image segmentation is first undertaken by the Hard C-mean technique in a crisp sense with the calculation of the initialization matrix, the center vectors, the distance matrix, and the membership grade matrix. 2) One MRF model is then set up to construct and utilize the joint probability distributions of two components, i.e., the regional labeling and the local feature modeling. The regional labeling component imposes a homogeneity constraint and local spatial coherent interaction on the underwater image segmentation process, while the local feature modeling component formulates as fitting and approximating a variety of the characteristics in the underwater images. 3) We further try to seek for a balance between the two competitive components and provide the link between the priori knowledge and the uncertainty of description by a simulated annealing scheme, such that the spatial relationship could be taken into consideration to refine the underwater image segmentation process in the optimal criterion.

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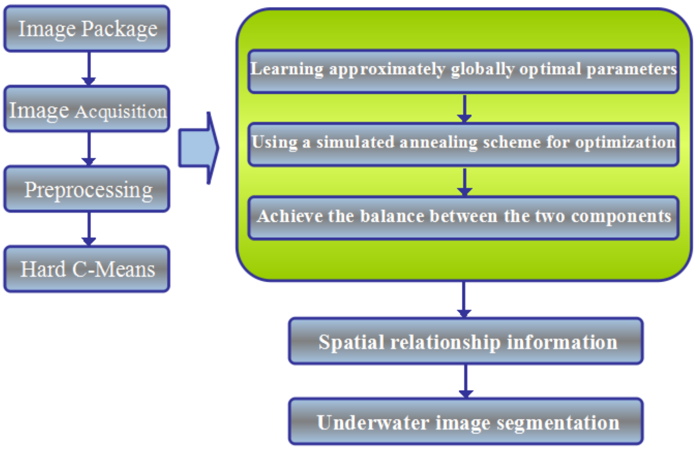


Fig. 1. The flow chart of Underwater Image Segmentation

III. HARD C-MEANS METHOD

Hard C-means is the initial underwater image segmentation method to find clusters and cluster centers in a set of unlabeled pixels in the underwater image. The number of cluster centers C is a priori known and iteratively moves the centers to minimize the total cluster variance.

The goal is to find the class centers that minimize the objective function given by the following equation:

$$J=\sum_{i=1}^{c} J_i=\sum_{i=1}^{c}\sum_{k,x_k\in C_i} d(x_k,C_i) \tag{1}$$

where C_i is the center of the i th class; $d(x_k,C_i)$ is the distance between i th center C_i and k th set of underwater image pixels X.

We use the Euclidean distance to define the objective function by:

$$J=\sum_{i=1}^{c} J_i=\sum_{i=1}^{c}\left(\sum_{k,x_k\in C_i}\left\|x_k-C_i\right\|^2\right) \tag{2}$$

Given a underwater image $X=\{x_1,x_2,...,x_n\}$, where $x_k=[x_{k1},x_{k2},...,x_{km}]$, n and m are the underwater image height and width in pixels. Let $P(X)$ be the power set of X, that is, the set of all the subsets of X. A hard c-partition of X is the family $\{A_i\in P(X):1\le i\le c\}$ such that

(1) $A_i\ne\varnothing, i=1,...,c$;

(2) $\bigcup_{i=1}^{c} A_i=X$;

(3) $A_i\bigcap A_j=\varnothing; i,j=1,...,c$ and $1\le i\ne j\le c$.

Here c is the number of clusters. Each A_i is viewed as a cluster. The hard c-partition can be reformulated through the characteristic function of the element x_k in A_i, define that

$$u_{ik}=\begin{cases}1 & x_k\in A_i\\ 0 & x_k\notin A_i\end{cases} \tag{3}$$

where $x_k\in X, A_i\in P(X), i=1,2,...,n$. Given the value of u_{ik}, we can uniquely determine a hard c-partition of X. The elements of the partition matrix u_{ik} satisfy the following three conditions

$$u_{ik}\in\{0,1\}, 1\le i\le c, 1\le k\le n \tag{4}$$

$$\sum_{i=1}^{c} u_{ik}=1, \forall k\in\{1,2,...,n\} \tag{5}$$

$$0<\sum_{k=1}^{n} u_{ik}<n, \forall k\in\{1,2,...,c\} \tag{6}$$

At the interpretation end, Eq.(4)and Eq.(5) mean that each $x_k\in X$ should belong to one and only one cluster. Eq.(6) requires that each cluster A_i must contain at least one and at most $n-1$ pixels. Collecting u_{ik} with $1\le i\le c$ and $1\le k\le n$ into a $c\times n$ matrix $U=[u_{ik}]$. We obtain the matrix representation for hard c-partition, defined as follows.

$$M_c=\left\{U \,\middle|\, u_{ik}\in\{0,1\}, \sum_{i=1}^{c} u_{ik}=1, 0<\sum_{k=1}^{n} u_{ik}<n\right\} \tag{8}$$

The steps for HCM is as follows:

Step1: Fix the number of clusters c $(2\le c<n)$ and initialize the partition matrix $U^{(0)}\in M_c$.

Step2: Calculate the center vectors v_i of each cluster:

$$v_i^{(r)}=\{v_{i1},v_{i2},...,v_{ij},...,v_{im}\} \tag{9}$$

$$v_{ij}^{(r)}=\frac{\sum_{k=1}^{n} u_{ik}^{(r)}\times x_{kj}}{\sum_{k=1}^{n} u_{ik}^{(r)}} \tag{10}$$

where $[u_{ik}]=U(r)$, $i=1,2,...,c$, $j=1,2,...,m$.

Step3: Update the partition matrix $U^{(r)}$.

$$d_{ik}=d(x_k-v_i)=\|x_k-v_i\|=\left[\sum_{j=1}^{m}(x_{kj}-v_{ij})^2\right]^{1/2} \tag{11}$$

$$u_{ik}^{(r+1)}=\begin{cases}1 & d_{ik}^{(r)}=min\{d_{jk}^{(r)}\}, j\in c\\ 0 & otherwise\end{cases} \tag{12}$$

Step4: Check a termination criterion. If $\left\|U^{(r+1)}-U^{(r)}\right\|\le\varepsilon$, stop; otherwise, set $r=r+1$ and return to Step 2.

However, There is a large problem with underwater images what might have wrong intensity. So different features in underwater image such as priori information, texture, contextual, spatial are needed to provide a good segmentation result for underwater images.

IV. SEGMENTATION MODEL

A. MRF basics

In this paper, we make use of MRF method which is one of the powerful methods for incorporating of different properties in underwater image segmentation. In MRF, segmentation problem turns into the labeling problem, then best label field is seek for final results.

Let $S=\{s=(i,j)\,|\,1\le i\le r, 1\le j\le c\}$ be the set of underwater image lattice sites. A neighborhood system N for the lattice S is also defined as $N=\{N_s, s\in S\}$ where $s\notin N_s$ and $r\in N_s \Leftrightarrow s\in N_r$.

A random field X is said to a MRF on S with respect to a neighborhood system $N=\{N_s, s\in S\}$ if and only if

(1) $P(X=x)>0, \quad \forall x \in W_X$

(2) $P(X=x_s|X=x_{S-\{s\}})=P(X=x_s|X=x_{N_s})$

where W_X is the set of all possible x on S and $S-\{i\}$ denotes the set difference. The condition means that only neighboring labels have direct interaction with each other, and the joint probability $P(X=x)$ can be uniquely determined by its local conditional probabilities.

The Hammersley-Clifford theorem allows us to assume the Markov-Gibbs equivalence between the probabilities of the local characteristics in an MRF and local energy potentials in a Gibbs distribution as follows:

$$P(X=x)=\frac{1}{Z}e^{-\frac{1}{T}U(x)} \tag{13}$$

where Z is the normalization factor called partition function, T is the temperature parameter. $U(x)=\sum_{c\in S}V_c(x)$ is the energy function, where $V_c(x)$ is a clique potential function over all cliques in underwater image $c\in S$.

B. A simple MRF based segmentation model

Denote the feature vector extracted from a random underwater image $X=x$ by $F=f$, where F denotes a random variable. Suppose there are K components in the feature vector $f=\{f_k|k=1,2,...,K\}$. For each pixel s, the region-type that the pixel belongs to is specified by a class label $Y=\{y_s, s\in S\}$, which is modeled as a discrete random variable taking values in a common label space $\Lambda=\{1,2,...,L\}$ where L is the number of classes. The set of underwater image labels Y is a random field. According to the Bayes rule, the segmentation problem is formulated as

$$P(Y=y|F=f)=\frac{\prod_{k=1}^{K}P(F=f_k|Y=y)P(Y=y)}{P(F=f)} \tag{14}$$

where $P(Y=y|F=f)$ is the posteriori probability of $Y=y$ conditioned on $F=f$, $P(F=f_k|Y=y)$ stands for the probability distribution of the extracted feature component f_k conditioned on the underwater image segmented result $Y=y$. $P(F=f)$ is the probability distribution of $F=f$, and $P(Y=y)$ is a priori probability of $Y=y$, which describes the label distribution of a segmented result only and is normally referred to as the region labeling component in underwater image.

Basically, the underwater image process F represents the deviation from the underlying label process Y. Thus, the overall segmentation model is composed of the hidden label process Y and the observable noisy underwater image process F. The next step is to find the optimal label configuration Y^* that maximizes $P(Y=y|F=f)$. This is known as the maximum a posteriori(MAP) solution.

C. MAP-MRF objective function

From the viewpoint of MAP estimation, the optimal labeling Y can be obtained by solving the following equation:

$$Y^*=arg\ max\, P(Y|F)=arg\ max\{P(F|Y)P(Y)\} \tag{15}$$

Considering Potts model, we notice that when there is no spatial interaction between sites of underwater image it comes

$$P(Y)=\frac{e^{-U(y_s)}}{\sum_{y_s\in\Lambda}e^{-U(y_s)}} \tag{16}$$

$$U(y_s)=\sum_{c\in S}V_c(y_s)=\sum_{j\in N_s}[\delta(y_s,y_j)-1] \tag{17}$$

$$\delta(y_i,y_j)=\begin{cases}1 & y_i=y_j\\ 0 & y_i\neq y_j\end{cases} \tag{18}$$

so that $U(y_i)$ can be related to a priori weights accounting for the relative importance of Y at site i.

Although the underwater image features extracted often vary due to the existence of noise and a non-stationary distribution of pixels, the Gaussian function can still be used to approximate it since a unimodular distribution is expected. Here, it is to assume feature of underwater image be a Gaussian function with different means μ_l and standard deviations σ_l. That is,

$$P(F=f_k|Y=y)=\frac{1}{\sqrt{2\pi\sigma_l}}e^{-\frac{(f_k-\mu_l)^2}{2\sigma_l^2}} \tag{19}$$

Because of the highly complicated interactions among multiple labels, we adopt a local search method called iterated conditional modes(ICM) to solve the joint probability $P(F=f_k|Y=y)$. According to Gibbs distribution,

$$P(Y=y|F=f_k)=\frac{1}{Z_1}e^{-U(Y=y|F=f_k)} \propto e^{-U(Y=y|F=f_k)} \tag{20}$$

$$P(Y|F)=\frac{P(F|Y)P(Y)}{P(F)} \propto P(F|Y)P(Y) \tag{21}$$

Substitute Eq.(13), we could derive that:

$$U(Y|F)=U(F|Y)+U(Y)=-lnP(F|Y)+U(Y)-lnZ_1 \tag{22}$$

Maximize $P(F=f_k|Y=y)$ is equivalent to minimize Eq.(23). We adopt ICM algorithm to update y_s sequentially via minimize $U(y_s|y_{N_s}^{(n)},X)$. It yields：

$$y_s^{*(n+1)}=arg\ min\{U(y_s|y_{N_s}^{(n)},f)\} \tag{23}$$

V. STABLE MRF-BASED METHOD

In this paper,In this paper, the pixel s of the underwater image is denoted to the position of the particle. The optimum solution can be solved during the iteration. This can decreases the computational complexity of the conventional MRF methods by combining clustering and MRF method. The procedure is described as below:

Step1: A random segmentation underwater image is initialized by HCM algorithm. Although the clustering methods are sensitive to noise and intensity of underwater image pixels, the pixels with high membership degree to each cluster have high possibility to be in the right segment.

Step2: Estimate μ_l and σ_l from the feature set $F=f_k$ based on the segmented underwater image:

$$\mu_l^m=\frac{1}{N}\sum_{k\in K,\ y_s=l}f_k^m \tag{24}$$

$$\sigma_l^m=\left[\frac{1}{N-1}\sum_{k\in K,y_s=l}(f_k^m-\mu_l^m)^2\right]^{\frac{1}{2}} \tag{25}$$

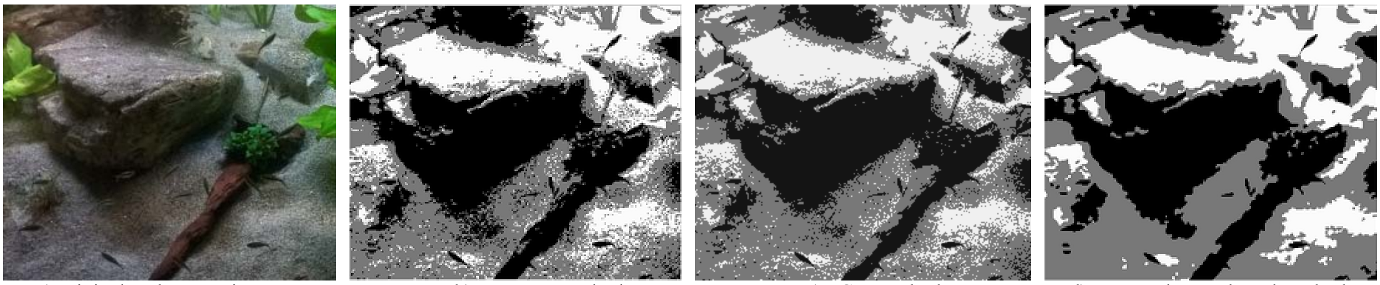
Step3: Use the estimated μ_l and σ_l to obtain a refined segmentation underwater image by minimizing Eq.(23).

Step4: Repeat Step2, 3 until stopping criterion is satisfied.

The regions with complex boundaries and noise samples in the underwater image will be finally selected via Step2 to Step4.

VI. SIMULATION EXPERIMENT

In our simulation experiments, underwater video recordings were collected by a Myring streamline AUV system with an average submergence depth of 2-3 meters. All the simulation experiments are implemented using MATLAB R2012a on a computer with 64-bit Windows 7, 2.67 GHz Intel Core i7 CPU, and 4 GB RAM. K-means clustering and FCM clustering have been used here in comparison. Fig. 3(a) is the original underwater image acquired by our platform, Fig. 3(b) is the segmented result of K-means method, Fig. 3(c) is the segmented result of FCM method, Fig. 3(d) is the segmented result of proposed method in this paper. It has been shown that the proposed approach is superior in both robustness and effectiveness, and behaves good vision effects in the underwater image segmentation.



a) original underwater image b) K-means method c) FCM method d) proposed MRF-based method

Fig. 3. The underwater image segmentation result

VII. CONCLUSIONS

In this paper, one robust and efficient underwater image segmentation method has been present here by combining Hard C-means clustering and MRF. The Hard C-means clustering is used for initial segmentation and approximation of MRF parameters, and MRF is further applied for the smoothness of segmentation. This method combines the region labeling component and the feature modeling component in a simple MRF based on the selection of subset of underwater image pixels. It has been indicated in the simulation experiment that the proposed approach performs the underwater image segmentation in the visual effectiveness, accuracy, and stability for the underwater images.

ACKNOWLEDGEMENTS

This work is partially supported by the Natural Science Foundation of P. R. China (31202036), the National Science & Technology Pillar Program (2012BAD28B05), the National High-Tech R&D 863 Program (2014AA093410), the Key Science & Technology Project of Shandong Province (2013GHY11507), the Fundamental Research Funds for the Central Universities (201362030), and the Natural Science Foundation of P. R. China (41176076, 51379198,51075377).

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