UNSUPERVISED MARKOVIAN SEGMENTATION OF SONAR IMAGES

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ABSTRACT

This work deals with unsupervised sonar image segmentation. We present a new estimation segmentation procedure using the recent iterative method of estimation called Iterative Conditional Estimation (**ICE**). This method takes into account the variety of the laws in the distribution mixture of a sonar image and the estimation of the parameters of the label field (modeled by a Markov Random Field (**MRF**)). For the estimation step we use a maximum likelihood estimation for the noise model parameters and the least square method proposed by Derin *et al.* to estimate the **MRF** prior model. Then, in order to obtain a good segmentation and to speed up the convergence rate, we use a multigrid strategy with the previously estimated parameters. This technique has been sucessfully applied to real sonar images and is compatible with an automatic treatment of massive amounts of data.

1. INTRODUCTION

Due to its high-resolution performance a high frequency sonar allows to visualize all kind of objects located on the sea-bottom. Their detection and then their classification (as wrecks, rocks, man-made objects, and so on...) are based on the extraction and identification of their associated projected shadows in sonar picture. Before any neuronal classification step, the processing chain has previously to segment the sonar image between *shadow area* and *sea-bottom reverberation area*. Nevertheless, segmenting an image into different classes without *a priori* information is not an easy task in computer vision. The main difficulty is that the parameter estimation is required for the segmentation, while the segmentation is needed for the parameter estimation. For example a Markovian segmentation [1] [2] gives good results; nevertheless a large number of estimated parameters is required in order to solve the problem of unsupervised segmentation of image sonar.

To circumvent this difficulty, a scheme was proposed in [3] in which the estimation and the segmentation are implemented recursively. This method is interesting but requires a very complicated computation. An alternate approach to solve the unsupervised **MRF** segmentation problem consists in having a two steps process. First a parameter *estimation step* in which we have to estimate the noise model parameter and the **MRF** model parameters. Then a second step in which we applied the segmentation algorithm with the estimated parameters.

First let us consider the estimation of the noise model parameters. Several techniques were proposed previously to determine a Maximum Likelihood estimate of the noise model parameters from a given image. **EM** (*Expectation Maximization*) or **SEM** algorithms (*Stochastic Expectation Maximization*) can be used in the case of Gaussian distribution mixtures [4] [5] or for a specific application to sonar imagery where we take into account the variety of laws in the distribution mixture [6]. Nevertheless, these algorithms do not take into account the properties of the label field defined in a **MRF** segmentation as a Gibbs distribution. As we will show in this paper, another way to estimate these parameters consits in using the **ICE** procedure.

Let us consider now the estimation of the **MRF** model parameters. The **MRF** model provides a powerful tool for incorporating the knowledge about the spatial dependence of each label of the segmented image. The knowledge about the scene is incorporated into an energy function that consists of apropriate clique functions. In most of the previous work using **MRF** models, the parameters of the prior model are assumed to be known and determined in an *ad hoc* fashion. However the values of these parameters determine the distribution over the configuration space to which the system converges. Besides, in our application, it is difficult to find appropriate parameters values of the clique functions since the real scenes are different for each picture (sea floor with pebbles, dunes, ridges, sand, ...). Thus estimating these parameters is very crucial in practice for successful labelling.

In this paper, we adopt for the *Estimation Step* the general and recent **ICE** procedure to estimate simultaneously the **MRF** prior model (with the Least Square estimator **LSQR** described by Derin *et al*) and the noise model parameters (with a Maximum Likelihood estimator). For the *Segmentation Step*, we use a multigrid segmentation with the previously estimated parameters. This paper is organized as follows : In section 2 and 3, we define the notation and we give a brief description of the **ICE** procedure and the used estimators. Section 4 and 5 detail the *Estimation Step* and the initialization of the procedure. The experimental results on real scenes are presented in section 6.

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2. ITERATIVE CONDITIONAL ESTIMATION

We consider a couple of random fields $Z = (X, Y)$, with $Y = \{Y_s, s \in S\}$ the field of observations located on a lattice S of N sites s and $X = \{X_s, s \in S\}$ the associated labelling. Each of the Y_s takes its value in $\Lambda_{obs} = \{0, \ldots, 255\}$ and each X_s in $\{e_0 = shadow,\ e_1 = sea\ bottom\ reverberation\}$. The distribution of (X, Y) is defined by, firstly, $P_X(x)$, the distribution of X which is supposed stationary and Markovian and, secondly, the distributions $\Pi_s P_{Y_s/X_s}(y_s/x_s)$. In this work these distributions vary with the class.

In the unsupervised segmentation case, we have to estimate in a first step (*Estimation Step*), parameter vectors Φ_x and Φ_y which define $P_X(x)$ and $P_{Y/X}(y/x)$ respectively. We estimate them using the iterative method of estimation called Iterated Conditional Estimation (**ICE**) [7]. This method requires to find two estimators, namely $\hat{\Phi}_x = \Phi_x(X)$ and $\hat{\Phi}_y = \Phi_y(X, Y)$ for completely observed data. When X is unobservable, the iterative **ICE** procedure defines $\Phi_x^{[k+1]}$ and $\Phi_y^{[k+1]}$ as conditional expectations of $\hat{\Phi}_x$ and $\hat{\Phi}_y$ given $Y = y$ computed according to the current values $\Phi_x^{[k]}$ and $\Phi_y^{[k]}$. These are the best approximations of Φ_x and Φ_y in terms of the mean square error. By denoting E_k, the conditional expectation using $\Phi^{[k]} = [\Phi_x^{[k]}, \Phi_y^{[k]}]$. This iterative procedure is defined as follows :

- One takes an initial value $\Phi^{[0]} = [\Phi_x^{[0]}, \Phi_y^{[0]}]$.
- $\Phi^{[k+1]}$ is computed from $\Phi^{[k]}$ and $Y = y$ by :

$$\Phi_x^{[k+1]} = E_k[\hat{\Phi}_x | Y = y] \quad (1)$$

$$\Phi_y^{[k+1]} = E_k[\hat{\Phi}_y | Y = y] \quad (2)$$

The computation of these expectations is impossible in practice, but we can approach (1) and (2), thanks to the law of large numbers by :

$$\Phi_x^{[k+1]} = \frac{1}{n} \cdot [\Phi_x(x_{(1)}) + \cdots + \Phi_x(x_{(n)})] \quad (3)$$

$$\Phi_y^{[k+1]} = \frac{1}{n} \cdot [\Phi_y(x_{(1)}, y) + \cdots + \Phi_y(x_{(n)}, y)] \quad (4)$$

Where $x_{(i)},\ i = 1, \ldots, n$ are independent realizations of X according to the distribution $P_{X/Y, \Phi^{[k]}}(x/y, \Phi^{[k]})$. Finally, we can use the **ICE** procedure for our application because we get :

- An estimator $\Phi_y(X, Y)$ of the *complete data* : we use a Maximum Likelihood (**ML**) estimator for the noise model parameter estimation. In order to estimate $\hat{\Phi}_x = \Phi_x(X)$, given a realization x of X, we use the **LSQR** estimator [8] described by Derin *et al.* which will be exposed (see subsection 3.2).
- An initial value $\Phi^{[0]}$ not *too far* from the real parameter (see section 4).
- A way of simulating realizations of X according to the posterior distribution $P_{X/Y}(x/y)$ by using the Gibbs sampler [9].

The **ICE** procedure is not limited by the form of the conditional distribution of the noise. This algorithm is well adapted for our application where the speckle distribution in the sonar images is not exactly known and varies according experimental conditions.

3. ESTIMATION OF PARAMETERS

3.1. Noise Model Parameters

The Gaussian law, $\mathcal{N}(\mu, \sigma^2)$ is an appropriate degradation model to describe the luminance y within *shadow* regions (essentially due to the electronical noise). The more natural choice of the estimator $\hat{\Phi}_y = \Phi_y(x = e_0, y)$ is the empirical mean μ and variance σ^2 :

$$\hat{\mu}_{ML} = \frac{1}{N} \cdot \sum_{i=1}^{N} y_i \quad (5)$$

$$\hat{\sigma}^2_{ML} = \frac{1}{N-1} \cdot \sum_{i=1}^{N} (y_i - \hat{\mu}_{ML})^2 \quad (6)$$

In order to take into account the speckle noise phenomenon [10], we model the conditional density function of the *sea bottom* class by a shifted Rayleigh law $\mathcal{R}(min, \alpha^2)$ [6]. The maximum value of the log-likelihood function is used to determine a Maximum Likelihood estimator of the *complete data*. If $\hat{y}_{min}$ is the minimum grey level within the *sea bottom* region, we obtain the following results :

$$\hat{\alpha}^2_{ML} = \frac{1}{2N} \cdot \sum_{i=1}^{N} (y_i - \widehat{min}_{ML})^2 \quad (7)$$

$$\widehat{min}_{ML} \approx \hat{y}_{min} - 1 \quad (8)$$

3.2. A Priori Model Parameters

A **MRF** prior model is specified in terms of certain parameters, called the clique parameters. These parameters correspond to the clique potential values of an equivalent Gibbs Random Field representation. Several schemes have been proposed in the computer vision literature for the estimation of the **MRF** parameters. Most of them (coding method, maximum pseudo likelihood method [1] ...) are iterative and have to solve a set of nonlinear equations.

The **MRF** parameter estimation method described in this section has been proposed by Derin *et al.* This scheme is not iterative and parameters estimated are close to the true parameters [8]. We briefly describe this estimator in terms of our model, *i.e.* the eight nearest neighborhood system. Let η_s represent the set of labels assigned to the neighbors of site s and $\mathbf{\Phi}_x = [\beta_1, \beta_2, \beta_3, \beta_4]$ be the *a priori* parameter vector (clique potentials) (see Fig. (1)). We define :

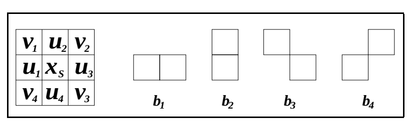

Figure 1: *Eight neighborhood and associated cliques*

$$\mathbf{\Theta}^t(x_s, \eta_s) = [\mathcal{I}(x_s, u_1) + \mathcal{I}(x_s, u_3), \mathcal{I}(x_s, u_2) + \mathcal{I}(x_s, u_4), \mathcal{I}(x_s, v_1) + \mathcal{I}(x_s, v_3), \mathcal{I}(x_s, v_2) + \mathcal{I}(x_s, v_4)]$$

Where $$\mathcal{I}(z_1, z_2) = \begin{cases} 0 & \text{if } z_1 = z_2, \\ 1 & \text{otherwise.} \end{cases}$$

The local energy function U can be expressed as :

$$U(x_s, \eta_s, \mathbf{\Phi}_x) = \mathbf{\Theta}^t(x_s, \eta_s) \cdot \mathbf{\Phi}_x \quad (9)$$

The local conditional probability at site s can be written :

$$P_{X_s/X_{\eta_s}}(x_s/\eta_s) = \frac{P_{X_s,\eta_s}(x_s,\eta_s)}{P_{X_{\eta_s}}(\eta_s)} = Z_s^{-1} \cdot \exp^{-U(x_s,\eta_s,\mathbf{\Phi}_x)}$$

Where Z_s is the local partition function and $P(e_1, \eta_s)$ is the joint distribution of the label e_1 with the neighborhood η_s. We obtain the following expression for two different values of x_s ($x_s = e_0$ and $x_s = e_1$) with identical neighborhood η_i :

$$\exp[-U(e_1, \eta_i, \mathbf{\Phi}_x) + U(e_0, \eta_i, \mathbf{\Phi}_x)] = \frac{P_{X_s,X_{\eta_s}}(e_1,\eta_i)}{P_{X_s,X_{\eta_s}}(e_0,\eta_i)}$$

Taking logarithms on both sides and substituting for U from (9), we have :

$$[\mathbf{\Theta}(e_0, \eta_i) - \mathbf{\Theta}(e_1, \eta_i)]^t \cdot \mathbf{\Phi}_x = \ln\left[\frac{P_{X_s,X_{\eta_s}}(e_1,\eta_i)}{P_{X_s,X_{\eta_s}}(e_0,\eta_i)}\right] \quad (10)$$

$\mathbf{\Phi}_x$ is the unknown parameter vector to be estimated and the ratio of the right hand side of (10) may be estimated using simple histogramming (by counting the number of 3×3 blocks of type (e_1, η_i) and dividing by the number of blocks of type (e_0, η_i) over the image). By substituing each value of η_i with (10), we obtain 256 equations (2^8 possible neighborhood configurations) in four unknowns. This overdetermined linear system of equations is solved with the least square method.

4. INITIALIZATION

The initial parameter values have a significant impact on the rapidity of the convergence of the **ICE** procedure and on the quality of the final estimates. In our application, we use the following method :

The initial parameter of the noise model $\Phi_y^{[0]}$ are determined by applying a $6 * 6$ non overlapping sliding window over the image and calculating the sample mean, variance and minimum grey level estimates. Each estimation calculated over the sliding window gives a sample $\mathbf{x}_i$ (in fact a three dimension vector). These (unlabelled) samples $\{\mathbf{x}_1, \ldots, \mathbf{x}_M\}$ are then clustered into two classes using the **K-means** clustering procedure in the following way :

1. Choose K initial cluster centres $c_1^{[1]}, \ldots, c_K^{[1]}$.
   These could be arbitrary, but are usually defined by:
   $$c_i^{[1]} = \mathbf{x}_i \qquad 1 \le i \le K$$
2. At the k^{th} step, assign the sample $\mathbf{x}_l$, $1 \le l \le M$ to cluster j if
   $$\| \mathbf{x}_l - c_j^{[k]} \| < \| \mathbf{x}_l - c_i^{[k]} \|$$
   for all $i \neq j$. In our application, the measure of similarity between two samples is the Euclidean distance.
3. Let $C_j^{[k]}$ denote the j^{th} cluster after Step 2. Determine new cluster centres by :
   $$c_j^{[k+1]} = \frac{1}{N_j} \cdot \sum_{\mathbf{x} \in C_j^{[k]}} \mathbf{x}$$
   Where N_j = number of samples in $C_j^{[k]}$. Thus, the new cluster centre is the mean of the samples in the old cluster.
4. Repeat until convergence is achieved ($c_j^{[k+1]} = c_j^{[k]} \; \forall j$)

In our application $K = 2$. **ML** estimation are then used over the **K-means** segmentation to find $\Phi_y^{[0]}$. The initial parameters of the Gibbs distribution are obtained by using the **LSQR** method from the **ML** segmentation $\hat{x}^{[0]}$.

$$\begin{aligned} \Phi_x^{[0]} &= \Phi_{\text{LSQR}}(\hat{x}^{[0]}) \qquad \text{with} \\ \hat{x}_s^{[0]} &= \arg\max_{x_s} P_{Y_s/X_s,\Phi_y^{[0]}}(y_s/x_s, \Phi_y^{[0]}) \quad (\forall s \in S) \end{aligned}$$

5. PARAMETERS ESTIMATION PROCEDURE

We can use the following algorithm to solve the unsupervised sonar image segmentation problem. Remind us that this method takes into account the diversity of the laws in the distribution mixture estimation as well as the problem of the estimation of the label field parameters.

- **Initialization** : **K-mean** algorithm (see section 4). Let us denote $\Phi^{[0]} = [\Phi_x^{[0]}, \Phi_y^{[0]}]$ the obtained result.
- **ICE procedure** :
  $\Phi^{[k+1]}$ is computed from $\Phi^{[k]}$ in the following way :
  – Using the Gibbs sampler, n realizations $x_{(1)}, \ldots,$ $x_{(n)}$ are simulated according to the posterior distribution with parameter vector $\Phi^{[k]}$, with :

  $P_{Y_s/X_s}(y_s/x_s = e_0)$ a Gaussian law (shadow aera)
  $P_{Y_s/X_s}(y_s/x_s = e_1)$ a Rayleigh law (sea bottom aera)

  – For each $x_{(i)}$ $(i = 1, \ldots, n)$, the parameter vector Φ_x is estimated by the Derin *et al.* algorithm and Φ_y with the **ML** estimator of each class.
  – $\Phi^{[k+1]}$ is obtained from $(\Phi_x(x_{(i)}), \Phi_y(x_{(i)}, y))$ $1 \le i \le n$ by (3) and (4).

If the sequence $\Phi^{[k]}$ becomes steady, the **ICE** procedure is ended and one proceeds to the segmentation using the estimated parameters.

6. SEGMENTATION ON REAL PICTURES

The energy function is complex and the **MAP** (Maximum a Posteriori) solution is difficult to estimate. In order to avoid local minima and to speed up the convergence rate, we use a multigrid strategy [11]. The observation field remains at the finest resolution, only the **MRF** model will be hierarchically defined. The parameters of the Gibbs distributions are adjusted automatically over scale.

We now present the different steps of our unsupervised segmentation method on real sonar images. Figure A_0 represents two original observations. Figure B_0 shows the result of the **K-means** clustering algorithm and Figure B_1, the representation of the two clusters associated to the *shadow* and *sea-bottom* classes. The mixture of distributions is represented by Figure C_0 and the final result of the segmented image is reported in Figure C_1. The obtained results are given in Table I.

7. CONCLUSION

We have described a novel unsupervised iterative estimation procedure based on the **ICE** algorithm which offers a good estimation of the noise model and Gibbs distribution parameters. This *Estimation Step* takes into account the diversity of the laws in the distribution mixture of a sonar image and can be used in a global estimation-segmentation procedure in order to solve the hard problem of unsupervised sonar image segmentation. This scheme is computationally quite simple, exhibits rapid convergence properties and should be well suited to automatic extraction of information from a large number of sonar images. This method has been validated on several real sonar images demonstrating the efficiency and robustness of this scheme. The extension of the method to unsupervised hierarchical segmentation (with inter-level connections) will be the topic of our research.

8. REFERENCES

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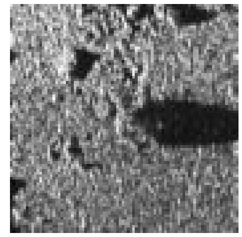

Fig A_0: sonar picture (object and rock shadows)

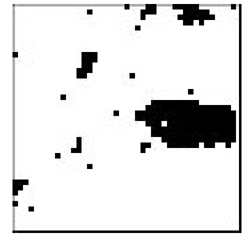

Fig B_0: K-means clustering procedure

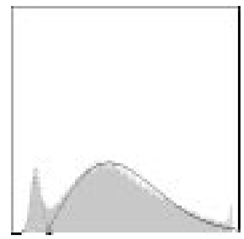

Fig C_0: Image histogram and estimated mixture

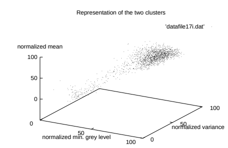

Fig B_1: representation of the two clusters

	Initialization : **K-means**			
$\Phi^{[0]}_{y(shadow)}$		$0.11_{(\pi)}$	$34_{(\mu)}$	$149_{(\sigma^2)}$
$\Phi^{[0]}_{y(sea-bottom)}$		$0.89_{(\pi)}$	$39_{(min)}$	$2830_{(\alpha^2)}$
$\Phi^{[0]}_{x}$	$1.2_{(\beta_1)}$	$1.7_{(\beta_2)}$	$-0.3_{(\beta_3)}$	$-0.2_{(\beta_4)}$
	ICE procedure			
$\hat{\Phi}_{y(shadow)}$		$0.10_{(\pi)}$	$28_{(\mu)}$	$34_{(\sigma^2)}$
$\hat{\Phi}_{y(sea-bottom)}$		$0.90_{(\pi)}$	$39_{(min)}$	$4960_{(\alpha^2)}$
$\hat{\Phi}_{x}$	$1.2_{(\beta_1)}$	$1.7_{(\beta_2)}$	$-0.2_{(\beta_3)}$	$-0.2_{(\beta_4)}$

Table I: estimated parameters. π stands for the proportion of the two classes within the sonar image. μ and σ^2 stands for Gaussian parameters (shadow area). min and α are the Rayleigh law parameters (sea floor reverberation). β_i's are the a priori parameters of the Markovian modeling. $\Phi^{[0]}$ represents the initial parameter estimates and the final estimates are written $\hat{\Phi}$.

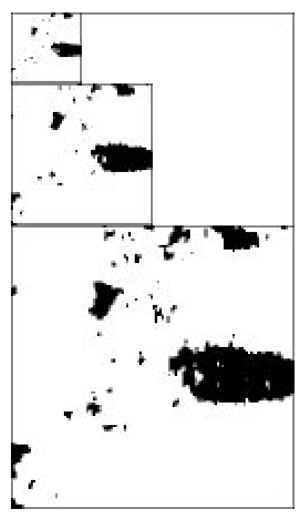

*Fig C_1: Multigrid **MAP** segmentation estimates with parameters obtained with **ICE** procedure*