Range and Acoustic Images

Restoration of Noisy Underwater Acoustic Images Using Markov Random Fields

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Abstract. This paper describes a method for the restoration of noisy underwater 3D acoustic images. A beamforming technique is used to build a 3D map associated with corresponding map representing the confidence (i.e., reliability) of measures. Backscattered echoes coming from a scene previously insonified are received by a two-dimensional array antenna and an image is formed, where each pixel represents the distance from the sensor in a specified direction. In the proposed algorithm, depth and confidence images are modelled as Markov Random Fields whose associated probability distributions are specified by a single energy functional, that embeds a-priori knowledge on the images and on the noise affecting measurements. Confidence measures are also considered to improve the restoration. Simulated Annealing is used to find the optimal MAP estimate of both images. Experimental results show the improvements in the resulting images as compared with initial data.

1. Introduction

Depth-map extraction is one of the most important tasks accomplished by active sonar systems to determine the range of an observed scene. Imaging systems using a single non-selective insonification of a scene and the beamforming of echoes backscattered and received by an array antenna are to be preferred in order to obtain a high frame rate (see [1,2]). The beamforming process provides a time signal representing the backscattered echoes generated by the scene in a particular direction. From the detection of the temporal instant corresponding to the highest peak (and assuming known sound velocity in water), it is possible to compute the distance of the scene in that direction. Iterating this mechanism for a set of regular directions forms a 3D image. The amplitude of the envelope of the output signal coming from the beamforming process also provides a reliability measure (we call "confidence value") of the depth estimate. The simplest method for extracting confidence measures from an envelope is to detect the maximum peak; however other statistical analyses can be made to detect the right peak of a received signal [3]. Speckle noise and other types of effects (e.g., reverberation) may affect backscattered echoes, thus modifying and attenuating the signal received by the antenna. As a consequence, it is not an easy task to detect the right time instants of peaks, then depth estimation becomes critical. Noise is generated by constructive and destructive interferences of the echoes diffused by a scene and can be approximated by Additive White Gaussian Noise [4]. Moreover, halos may form around objects, thus producing

high responses even in directions in which no object is present. This is due to the directivity characteristics of the antenna (i.e., side-lobe effects [5]). Eventually, these disturbing factors affect the estimation of the scene depth and give rise to images of the type shown in Fig. 2 (the ideal images are shown in Fig 1), where one can observe a non-null response where no object is present and null responses inside objects.

The goal of the proposed algorithm is to restore a range image modelled as a Markov Random Field (MRF) [6] using information available from a confidence map. The paper is organized as follows: in Section 2, the significance of the confidence map is pointed out, and, in Section 3, the MRF approach is described, with special emphasis on the energy functional. In Section 4, results are presented and discussed. Finally in section 5 conclusions are drawn.

2. The Confidence Map

To perform a correct estimation of a depth image, the envelope should have only one very high peak, representing the signal backscattered by a point of an object in a certain direction and received by an array antenna. The amplitude of this peak also provides a confidence value indicating the reliability of each depth estimate. The higher the peak, the higher the confidence. Denoting the envelope signal by V_0 , the depth image by Z , and the confidence image by S , different situations may occur when noise affects V_0 more or less strongly:

For points inside objects:

if V_0 presents a single high peak then the confidence S is high and the depth estimate Z is always correct. If V_0 presents a single weak peak and some fluctuations near zero the confidence is low but the depth estimate is equally correct because low noise make possible to detect the single peak of the envelope. If noise is high, V_0 has several similar peaks, then the right one might be confused with others; in this case, the estimate of the Z map may be wrong.

For points outside objects (or on object boundaries):

V_0 presents a low peak then the confidence S is low but non-zero, as the beamforming process give rises to artefacts (halos) on object boundaries (due to side lobes [5]). For these pixels the depth estimation is wrong, as the detected peak does not correspond to any object in the direction considered.

From these considerations, one can deduce that a depth value is correctly estimated only when the confidence value is high, but a low confidence value cannot confirm the depth measure, as the Z estimate may be correct or incorrect in dependence of noise effects.

A possible solution is to consider only those Z points whose confidence value are above a certain threshold. In this case side lobes can be removed, but many correct points inside objects are erroneously rejected as their confidence values are below the threshold. Then, a punctual analysis of the Z and S maps is not sufficient, and a coupled restoration of such maps is required.

3. The MRF Approach

Image restoration is considered as the problem to find the optimal configuration of a lattice field Y of random variables. To define an MRF is necessary to specify a probability distribution on a discrete field, where the probability of a random variable y_i depends only on a neighbouring set N_i :

$$p(y_i / Y) = p(y_i / y_j) \quad \forall y_j \in N_i$$

When an a-priori image model $p(Y)$ is of MRF type, and the observation model satisfies weak properties [6], an estimation of the solution Y is given by maximizing the a-posteriori probability of the field given observations X , which is known to be a Gibbs distribution (Hammersley-Clifford equivalence):

$$p(Y / X) = \frac{1}{Z_p} \cdot \exp \left[-\frac{E(Y / X)}{T} \right]$$

where $E(Y/X)$ is the energy function to be minimized, Z_p is the normalizing partition function, and T is the temperature of the field. The energy function $E(Y/X)$ can be written as a sum of local energies $E_p(Y/X) = \sum_c E_c(Y/X)$, where each energy $E_c(Y/X)$ depends only on the neighbouring system. To compute the MAP estimate, we need only to minimize $E(Y/X)$ by means of an optimization algorithm. We use simulated annealing to perform energy minimization, as the energy function may have many local minima. The energy functional is so composed by several terms linked to two types of information: the prior model and the sensor model of the depth and confidence maps Z and S . The global function embedding this information is:

$$E(Z, S / G_z, G_s) = E_p(Z) \cdot V_m^{(1)}(S) + E_p(S) + E_{obs}(Z / G_z) \cdot V_m^{(2)}(S) + E_{obs}(S / G_s)$$

where:

G_s and G_z are the observation fields of S and Z , respectively;

$E_p(Z)$, $E_p(S)$ are the functions related to the a-priori model of the fields Z and S ;

$V_m^{(1)}(S)$, $V_m^{(2)}(S)$ are the modulating functions of S that reinforce or weaken $E_p(Z)$ and $E_{obs}(Z/G_z)$ functions;

$E_{obs}(Z/G_z)$, $E_{obs}(S/G_s)$ derive from the models of the observations.

The components of the energy functional related to the Z field are those used in classical MRF algorithm for restoration and segmentation problems [7]. Assuming that g_{zi} is a generic pixel i of the observations, z_i is a generic pixel i of the depth lattice Z , s_i is a generic pixel i of the confidence lattice S , the energy functions are:

$$E_p(z_i, z_j) = (z_i - z_j)^2 \quad \forall z_j \in N_i \quad \text{and} \quad E_{obs}(z_i / g_{zi}) = \frac{1}{2} \cdot \sigma_z^{-2} \cdot (z_i - g_{zi})^2$$

where z_j is a generic pixel j of the neighboring set N_i .

In the proposed approach these terms are weighted by two functions of S .

The first function, modulating the a-priori model function of Z is:

$$V_m^{(1)}(s_i, s_j) = -K^{-2}(s_i \cdot s_j) + 1 \quad \forall s_j \in N_i$$

this function stresses the smoothness constraint if a generic pixel z_j , belonging to N_i , is low confident; in this case the observed image is unreliable and the only useful information is the prior model of the image.

The normalization value K is needed to restrict the function value between $\{0, 1\}$. The second function modulating the sensor model is:

$$V_m^{(2)}(s_i) = \sqrt{\frac{s_i}{K}}$$

this function reaches the maximum value, equal to 1, if the confidence of the pixel z_i is 1, stressing the observation constraint. For the function related to the prior model of S field, should be noted that the information on Z lattice is not useful for weighting the prior and sensor knowledge of confidence. In practice, the pixels of S are changed independently from the Z field, while the pixels of Z are varying taking into account the S information. The prior knowledge on S field should force the observed confidence map to become binary: 1 (maximum confidence) where an object is present and 0 otherwise. The function related to the prior model is:

$$E_p(s_i) = (s_i - s^*)^2$$

where the value s^* is calculated using a simple majority rule, with reference to a fixed threshold: s^* is equal to 1 if most of the pixels in the neighborhood of s_i are above this threshold, and is equal to 0 otherwise. A critical point of this algorithm is the choice of the confidence threshold: this value should be chosen carefully so as to preserve S values inside objects and to remove side lobe effects outside objects. For the sensor model of S , a Gaussian model is used, as previously done for the Z lattice.

4. Results and Discussion

The proposed algorithm was tested on simulated acoustic images provided by an active sonar simulator whose output signals had been processed by a beamforming algorithm. The goal of the algorithm was to restore the acoustic images in order to obtain an image similar to the ideal one shown in Fig.1a, starting from the noisy images in Fig.2a and Fig.2b (for depth and confidence, respectively). Fig.1a represents the ideal 2D projection of three objects located under the sea at different distance from the antenna. The three objects were a rectangular plate (20×30 cm) placed 5 meters far from the array and parallel to it; a square plate (20 cm side) placed 3.5 meters far from the array and inclined with respect to it; a spherical cap (30-cm diameter) placed 6.5 meters far from the array. The images were formed by means of 128×128 beams obtained by broad-band focused beamforming in quadrature in the time domain. The depth of each object is easily estimated according to the gray levels of the pixels: darker pixels correspond to shorter distances, and vice versa. Fig.1b shows the ideal confidence levels of the image; the confidence is high inside the objects and is null outside them. Fig.2a and 2b present real images obtained by the beamforming process; they are corrupted by speckle noise and the confidence map shows some “holes” inside the objects and side-lobe effects outside them. Fig.2c is an image obtained by keeping only the pixels of the Z image whose confidence values were above a fixed threshold. The image show many holes inside the objects. This proves that a punctual restoration is not sufficient. The proposed MRF algorithm uses the following parameters for the restoration process: size of input images: 128×128; 256 gray levels; second-order neighboring system;

logarithmic scheduling for temperature; confidence threshold level: 35. Fig.3a and 3b show the reconstructed depth image and the restored confidence image. The result is twofold: first, the algorithm removes holes and side-lobe effects inside and outside objects respectively; secondly, the final confidence map is a binary image that separates confident points from non-confident ones. After reconstructing the image, it was necessary to perform a further step. This processing was simply an AND operation on the restored confidence image in Fig. 3b. As a result, only confident points are present in the 3D image, and information about the object shapes can be simply derived from the restored confidence image. The final output image is shown in Fig.3c: one can notice a notable improvement over the image shown in Fig.2c. This result represents a good approximation to the ideal image shown in Fig.1a.

5. Conclusions

In this paper, we have presented a method that uses confidence information to restore underwater acoustic images. A-priori confidence information allows one to obtain a more accurate estimate of a depth image affected by speckle noise (modelled as AWGN) and to extract information about object shapes from the restored confidence image. To model both images, an MRF approach has been used, for which a single energy functional has been used. By minimizing this functional, the optimal estimate (in the MAP sense) has been found. We have shown that at each iteration, confidence values drive the restoration of noisy pixels of depth image, and, at the same time, confidence pixels, too, are restored; therefore both the 3D and confidence images are improved. Special attention has been given to the choice of the threshold for the confidence level.

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Fig. 1 (a) Ideal depth image; (b) ideal confidence image.

Fig. 2 Images resulting from the beamforming process and peak detection: (a) noisy depth image; (b) noisy confidence image; (c) AND between the depth and confidence images.

Fig. 3 Restored images: (a) restored depth image; (b) restored confidence image; (c) AND between the restored depth and confidence images.