Seabed geoacoustic characterization and classification by multisonar fusion

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SEABED GEOACOUSTIC CHARACTERIZATION AND CLASSIFICATION BY MULTISONAR FUSION

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1 INTRODUCTION

To improve the performance prediction of low frequencies sonar (Anti Submarine Warfare)we can use geoacoustic information coming from different kind of sensors. However, geoacoustic and scattering properties estimation by inversion of received acoustic signals remains very difficult and strongly dependent on the system of measurement. Indeed the interaction between an acoustic wave and the sediment is heavily dependent on frequency, measurement angle and micro roughness of seafloor. Therefore, fusion of geoacoustic models inverted from different sonar systems with wide diversity of insonification angles and frequencies (single beam echosounder (SBES), multibeam echosounder (MBES), sidescan sonar (SSS) and subbottom profiler(SBP)) allow an extended description of the acoustic properties of the seafloor and the first sediment layers.
In this paper, we propose a characterization method based on the Dempster Shafer theory of evidence to fuse geoacoustic models in order to classify the seafloor and estimate geoacoustic parameters.

2 COMBINED GEOACOUSTIC INVERSION AND FUSION PROCESS

The multi-sonars fusion approach for seabed geoacoustic characterization is described in figure 1. the use of different types of echosounders allows a wide diversity of insonification angles and frequencies. from the acoustical backscattered signals recorded by the MBES and SBES, geoacoustic parameters can be predict via an inversion process using a backscattering model. The next step is to fuse the predicted parameters to benefit of echosounders performances. To improve the final prediction parameters, the fused parameters can be re-utilized as a prior information for inversion step after a qualitative control achieved by analyzing the sediment structure from an SBP data.

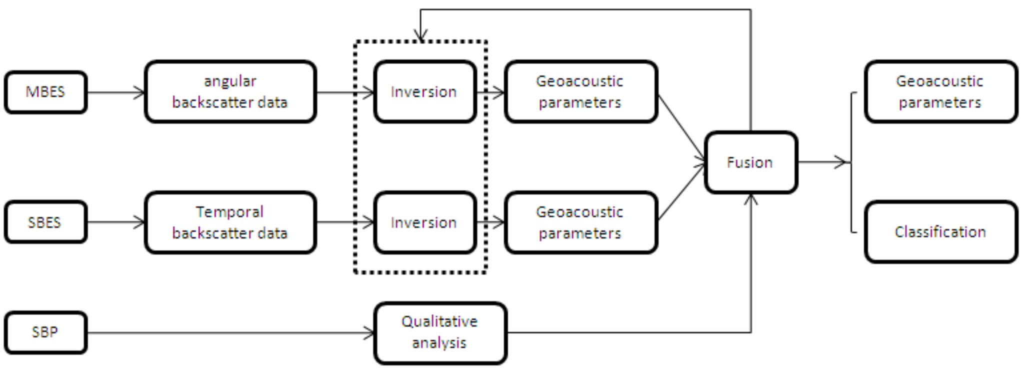

Figure 1: Inversion fusion process

3 THEORY OF BELIEF FUNCTIONS

The theory of belief function, also known as Dempster-Shafer Theory (DST), was developed by Shafer [1] and initiated by the work of Dempster on imprecise probabilities. It's one of the popular approches to handling uncertainty in literature for data fusion and it's often considered as a generalized model of probability and possibility theory. The theory may be summarized as follows.
Given a set of N mutually exclusive and exhaustive possible hypotheses, called frame of discernment, $\Theta = \{H_1, ..., H_N\}$, an elementary probability mass, called basic believe assignment (bba), can be assigned by means of data source for each single hypothesis or a set of hypotheses $A \subseteq \Theta (\Leftrightarrow A \in 2^{\Theta})$ such that:

$$m : 2^{\Theta} \rightarrow [0, 1] \tag{1}$$

and fulfils:

$$m(\phi) = 0 \tag{2}$$

$$\Sigma_{A \subseteq \Theta} m(A) = 1 \tag{3}$$

where $m(.)$ represents the mass function, ϕ is the empty set and the subset A such that $m(A) > 0$ is called a focal element.

3.1 EVIDENTIAL FUNCTIONS

By applying the mass function, the measure of total belief committed to $A \subseteq \Theta$ can be obtained by adding the mass of all subsets of A. It's given by the function *bel(.)* $: 2^{\Theta} \rightarrow [0, 1]$. There is:

$$\textit{bel}(A) = \sum_{\phi \neq B \subseteq A} m(B) \tag{4}$$

A belief function represents the lower limit of probability measurement and the following plausibility function provides the upper limit of probability *pl*$(.) : 2^{\Theta} \rightarrow [0, 1]$.

$$\textit{pl}(A) = \sum_{A \cap B \neq \phi} m(B) = 1 - \textit{bel}(\overline{A}) \tag{5}$$

where $\overline{A}$ is the complement of A.
A third evidential function called communality function $Q(.)$ was introduced by Shafer and it's defined as follows:

$$\textit{Q}(A) = \sum_{A \subseteq B} m(B) \tag{6}$$

when the basic assignment functions are defined only on Θ, the mass function $m(.)$ is then a Bayesian probability.

3.2 RULE OF COMBINATION

Under an iterative process, the Dempster's rule of combination between two independent sources of evidence expressed as two *bba* m_1 and m_2 forms a new body of evidence $m_{1,2}$ with witch the intersection between all focal elements are not empty. The normalize Dempster's rule of combination becomes,

$$m_{1,2}(A) = \frac{\sum_{C \cap B = A} m_1(C).m_2(B)}{1 - \sum_{C \cap B = \phi} m_1(C).m_2(B)} \tag{7}$$

The denominator of the combination rule is the cumulative degree of which the two pieces of evidence do not contradict with each other.

4 MASS FUNCTION ESTIMATION

One of the main difficulty of the DST is the estimation of the mass functions. In our case, we have as input in the fusion process geoacoustic parameters inverted from different kinds of sonars. Different seabed types show multi-modal distribution of geoacoustic parameters. For this reason, we will consider a problem of mixture models parameter estimation to manage uncertain data under Evidence theory.
In this section we present the mass function design.

4.1 LIKELIHOOD MODEL

This statistical learning model was proposed by Appriou in [2] and based on the likelihood function. For each data sources S_j, the mass function, satisfying three axioms, is defined by:

$$m_{kj}(\theta_k) = 0 \tag{8}$$

$$m_{kj}(\overline{\theta_k}) = q_{kj} * (1 - R_j * p(x_j/\theta_k)) \tag{9}$$

$$m_{kj}(\Theta) = 1 - q_{kj} + q_{kj} * R_j * p(x_j/\theta_k)) \tag{10}$$

where R_j is a normalization factor constrained by$R_j \in [0, (max_{k\in[1,K]} p(x_j/\theta_k))^{-1}]$, $\overline{\theta_k}$ is the complement of θ_k and q_{kj} are reliability coefficients on each data source j for each class k. q_{kj} is set to $q_{kj} = 1$ or $q_{kj} = 0.9$ according to the degree of confidence during the training phase and the normalized factor R_j is often taken us it's maximum value without justification in the literature.
The total masse function $m(.)$ is given by applying the Dempster's rule of combination for all m_{kj} functions as follow:

$$m_j(.) = \bigoplus_k m_{kj}(.) \tag{11}$$

$$m(.) = \bigoplus_j m_j(.) \tag{12}$$

where $\bigoplus$ symbol is the orthogonal sum of Dempster. The equation (11) represent the combination between all hypotheses of each source and equation (12) the combination of sources.

4.2 MAXIMUM LIKELIHOOD ESTIMATION

One of powerful method for finding maximum likelihood estimates of parameters in statistical models is the *expectation-maximization* algorithm, also called EM algorithm [3].In [4] the EM algorithm was used to estimate belief functions. Denoeux in [5] et [6] proposed a variant of the EM algorithm called the evidential EM (E^2M) algorithm in witch data uncertainty is represented by belief function.

In this article, we consider a problem of mixture models when the a priori probability function $p(X \mid \theta)$ supposed to be known. The likelihood function $L(\theta, X) = p(X \mid \theta)$ are estimated by means of the (E^2M) algorithm while mass functions assumed to be bayesian.The reader is referred to [6] for more detail.
To extend the EM algorithm to uncertain data, Denoeux propose to replace the marginal likelihood of the observed data $L(\theta, X)$ by the following expression:

$$L(\theta; pl) = \sum_{x\in\Theta_x} p_x(x;\theta) pl(x) \tag{13}$$

where the weighted coefficients $pl(x)$ is the contour function of an arbitrary mass function m. as noted in [6], we must distinguish between the probability mass function $p_x(x;\theta)$ which represents generic knowledge and $pl(x)$ witch represents uncertainly due to lack of knowledge. The probability mass function has the following expression:

$$p_x(x|pl;\theta) = \frac{p_x(x;\theta)pl(x)}{L(\theta;pl)} \tag{14}$$

In this article, each geoacoustic parameters vector $W_i = (w_i^1, ..., w_i^p)$ is assumed to be modeled by a normal distribution with mean μ_k and diagonal covariance Σ_k. Denoting by $\theta_k = (\mu_k, \Sigma_k)$ the parameters for each g classes, the aim is to estimate the unknown parameters representing the mixture of gaussians $\Phi = (\pi_1, ..., \pi_g, \theta_1, ..., \theta_g)$ where the complete data pdf is [6]:

$$p(x, \Phi) = \prod_{i=1}^{n} \prod_{k=1}^{g} (\pi_k \phi(w_i; \mu_k, \Sigma_k))^{z_{ik}} \tag{15}$$

z_{ik}'s are latent variables indicate which of the k classes each w_i had come from and $\phi(., \theta_k)$ is the normal distribution characterized by θ_k. the uncertainty about x is represented by:

$$pl(x) = \prod_{i=1}^{n} pl(z_i) pl(w_i) \tag{16}$$

where $pl(z_i)$ is the uncertainty on class labels and $pl(w_i)$ is the uncertainty on attributes w_i^j and assumed to be a normalized gaussian [6]:$pl(w_i^j) = \phi(w_i^j; m_i^j, (s_i^j)^2) s_i^j \sqrt{2\pi}$.
The EM algorithm is an iterative algorithm that has to steps. Applied in our problem, in the E-step, it tries to calculate the posterior probability using the current setting of our parameters $\Phi^{(t)}$. Using bayes rule, we obtain:

$$p_{ik}^{j(t)} = \frac{\pi_k^{(t)} pl_{ik} \prod_j \phi_{ik}^{j(t)}}{\sum_l \pi_l^{(t)} pl_{il} \prod_j \phi_{il}^{j(t)}} \tag{17}$$

with $\phi_{ik}^{j(t)} = \phi(m_i^j; \mu_k^{j(t)}, (\sigma_k^{j(t)})^2 + (s_i^j)^2)$. In the M-step, it updates the parameters of our model based on our guesses and values of our attributes are estimated by:

$$\mu_k^{j(t+1)} = \frac{\sum_{i=1}^{n} p_{ik}^{j(t)} \mu_k^{j(t)}}{\sum_{i=1}^{n} p_{ik}^{j(t)}} \tag{18}$$

5 EXPERIMENTAL RESULTS

To evaluate the proposed algorithm of fusion and *bba* estimation, we consider a problem of discrimination between three hypotheses in the case of two multibeam echosounders with two different frequencies $90\ khz$ and $30\ khz$. In order to link the measured MBES backscatter strength to each of the three hypotheses, Jackson geoacoustic model input parameters using grain size is employed according to [7]. The parameter space to be searched is 4-dimensional and are presented in table below.

Table 1: Model input parameters

Parameter	Description	Range
ϕ	Mean grain size	(-1)-9
ω_2	Strength of the bottom relief spectrum	(1e-7) - 0.5
σ_2	Volume parameter(dB)	(-60)-(-10)
β	Loss parameter(dB/λ)	(1e-4)-2

The fifth parameter of the model (Spectral exponent) is set to 3.25 during the simulation and the other parameters are used to simulated Gaussian data with $n = 200$ instances and the following values:

$\mu_1 = (1, 0.005587, -27, 0.898)$, $\mu_2 = (4, 0.001119, -28, 1.102)$, $\mu_3 = (7, 0.000518, -30, 0.132)$
$\Sigma_1 = (1, e-5, 1, e-3)$, $\Sigma_2 = (1, 1e-5, 1, 1e-3)$, $\Sigma_3 = (1.5, 1e-6, 1, 1e-4)$
$\pi_1 = \pi_2 = \pi_3 = 1/3$.

For each instance, we applied the direct Jackson model to calculate the bottom backscattering strength as a function of the grazing angle between $-75°$ and $75°$. The value of the backscattering strength was corrupted by a random value drawn from a Gaussian distribution with standard deviation of $2\ dB$. A non-linear least squares analysis using the Newton optimization technique is used to fit the noisy backscattering values

with Jackson model and to estimate the correspondent parameters . The whole experiment (noisy data and inversion) was repeated for the two different frequencies. For each obtained data set, the EM algorithm was applied to estimate the parameters of each class and to calculate the bba according to Appriou model. To simulate the uncertainty on attributes, the whole experiment was repeated 30 times for each instance and the uncertainty is set to the variance of each estimated attribute. the uncertainty on class label is set to $pl_{ik} = 1$ (in real case the uncertainty on class label can be estimated from Subbottom profiler data by exploring the thickness of the first sediment layer).
The estimated geoacoustics parameters obtained for each class after fusion are:

$$\mu_1 = 1.4327,\ 0.0131,\ -24.6137,\ 1.7745$$
$$\mu_2 = 3.6968,\ 0.0068,\ -27.8877,\ 1.1567$$
$$\mu_3 = 7.1683,\ 0.0014,\ -30.1474,\ 0.6916$$

with a recognition rate of $92,58\%$ if we consider the uncertainty on attributes and $84,77\%$ otherwise. we remark that the value estimated for each class is varying according to type of attributes. the first and third attributes are better estimated than the two other which are very difficult to observe for this model [8].

To improve the recognition rate using Appriou fusion model, the reliability coefficients q_{kj} on each data source j is estimated by the sum of the squares of the Backscattering strength deviations from the model prediction $\delta = \sum(BS_{pr} - BS)^2$ such that:

$$q_{kj} = 1 - 0.1 \times \frac{\delta}{max(\delta)} \tag{19}$$

With this method, the recognition rate is $93,076\%$ which is better than that found using $q_{kj} = 0.9$.

6 CONCLUSION

In this paper, we proposed a fusion inversion process for multi-sonars for seafloor characterization. The approach of fusion is based on the evidence theory witch can handle with the reliability of the echososunders and the uncertainty of the information to fuse. The next step of this work is to study the results of this approach on real data to assess the complementarities between geoacoustic parameters inverted from different echosounders.

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