Fusion of Local Statistical Detectors in SAS Imagery Classification

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Abstract—Detection of underwater mines is a present crucial strategic task. The images provided by Synthetic Aperture Sonar (SAS) are then of great interest for the detection and classification of objects lying on the sea floor or buried in the sea bed. This paper proposes a detection method based on data fusion, using local statistical characteristics extracted from the SAS data. These values come from first, second, third, and fourth order statistical properties of the sonar images.

I. INTRODUCTION

The detection and classification of different kinds of underwater mines is a present crucial strategic task. The mine hunting experts are looking for more and more efficient detection process in order to help them in decision (use of divers, detected mines destruction, etc.). For that, high level of technique systems are useful, specially in partially or completely buried objects detection. The goal of these process is to decrease as possible the number of false alarms (harmless objects detected as mines), while all the mines are detected.

Many approaches have been proposed in underwater mines detection and classification using sonar images. Most of them use the characteristics of the shadows projected by the objects on the sea bed [1] but are absent for buried objects. Among the approaches using the echoes, some of them are looking for enhancing them by filtering or isolating them by segmentation [2]. But these process are unsatisfactory in case of low signal to noise ratio (buried objects). Other propose fusion process by log-likelihood using mine models [3] or using neural networks [4]. The characteristics used in these process can be extracted from the sonar image [4] (these values can undergo an orthogonalisation [3]), the results from different sources [4], or different algorithms [5]. But the results coming from these processes are binary (mine / not mine) and let the expert without freedom in his decision. Indeed, the mine hunting experts search above all for algorithms helping them in their decision.

In this paper, we propose a detection method using a group of parameters extracted from a SAS image. Indeed, Synthetic Aperture Sonar (SAS) is a growing sonar system used in seabed imagery thanks to its high resolution useful for detection [6]. Considering the statistical properties of these SAS images, we will discuss on the use of statistical parameters locally performed on the image (section II). A fusion process using the evidence theory is then proposed in order to detect objects and classify them into “object” or “not object” (section III). Finally, the method is applied on real SAS data containing underwater mines lying on the sea bed, buried or partially buried in the sea floor, and the performance of this process is numerically evaluated (section IV).

II. EXTRACTION OF LOCAL STATISTICAL CHARACTERISTICS

A. Statistical properties of the SAS images

The sonar images, as any images formed by a coherent system (radar is an other example), are seriously corrupted by speckle giving a granular aspect. This noise comes from the presence of a large number of elements (sand, rocks,...) that are smaller than the wavelength, randomly distributed on the sea bed. The sensor receipts the result of the interference of all the waves reflected by the diffusers in a resolution cell. A Weibull law is then a good model for the amplitude $R$ of the background [1], [2]:

$$W_R(R) = \frac{\alpha}{\alpha} \left( \frac{R}{\alpha} \right)^{\delta-1} \exp \left\{- \left( \frac{R}{\alpha} \right)^\delta \right\} ; R \geq 0$$ (1)

with $\alpha$ a scale parameter and $\delta$ a shape parameter, strictly positive. These parameters can be easily estimated by a maximum likelihood estimator on the SAS image.

Considering the small number of pixels corresponding to the echoes on the SAS images, they are considered as deterministic elements surrounded by the noise background.

B. First and second order statistics: automated segmentation

A proportional relationship between the mean $\mu_R$ (1st order) and the standard deviation $\sigma_R$ (2nd order) can be extracted from the description of the background by a Weibull law:

$$\mu_R = k_w(\delta) \sigma_R$$ (2)

with

$$k_w(\delta) = \frac{\Gamma(1 + 1/\delta)}{\sqrt{\Gamma(1 + 2/\delta) - \Gamma(1 + 1/\delta)^2}}$$ (3)

$\Gamma$ being the Gamma function.
This interesting property, highlighted by the mean-standard deviation representation, is used in an automatic segmentation process on the SAS image [2]. This allows to isolate the reflected echoes from the background. The threshold evaluated by the segmentation, with the corresponding mean estimated by the proportionality relationship, can be used as characteristics in mine detection.

C. Higher order statistics

Third and fourth order statistics highlight interesting properties of the SAS images [7]. The most classically used values are the skewness (3rd order) and the kurtosis (4th order). If the rth central moment of the random sample X is denoted by \( \mu_X(r) \), the corresponding definitions of skewness \( \mathcal{S}_X \) and the kurtosis \( \mathcal{K}_X \) are:

\[
\mathcal{S}_X = \frac{\mu_X(3)}{\mu_X(2)^{3/2}} \quad \text{and} \quad \mathcal{K}_X = \frac{\mu_X(4)}{\mu_X(2)^{2}} - 3
\]

These values are locally estimated on the SAS image, by using a computation window moving all along the image. After a focalisation process, the results highlight the echoes, considered as deterministic elements, from the noise background where the skewness and the kurtosis are low. Moreover, these results are independent from the amplitude of the echoes.

III. DATA FUSION AND CLASSIFICATION

This paper concerns a detection method allowing to classify each pixel of the SAS image into "object" (likely to be a mine) or "not object". According to the previous section, the local statistical properties of the SAS images are interesting and relatively independent each other to be useful for detection and classification of the sought objects. But, these numerical data are of different values and kinds, and they cannot be then combined by a simple mathematical operator. This forces us to use data fusion tools.

A. Evidence theory

Many data fusion tools exist [8]. The most popular are the probability theory (with the bayesian theory), the neural networks, the possibility theory and the evidence theory. The first one is not adapted to our problem because of the difficulty in estimation of the probabilities corresponding to each parameter and because it does not take into account the uncertainty of the human judgment. The two last theories take into account both the imprecision and the uncertainty in the fusion process. The evidence theory [9] deals with both the imprecision and the uncertainty with mass functions. Moreover, it includes the "doubt" notion allowing the expert to take his decision in function of his own knowledge and experience. The evidence theory permits the detection of conflicts (sensors given opposite responses) and their management. The disadvantage of this theory is the combinator explosion in case of many hypothesis. In the concerned case, the number of hypothesis is only two: "object" and "not object".

\( \Omega = \{O, NO\} \) is the set of the hypothesis "object" (O) and "not object" (NO). The evidence theory defines the level of confidence given to the elements of \( \Omega \), and to the subsets of elements \( A \in 2^\Omega \) called propositions. An evidence mass \( m(A) \) is associated to \( A \in 2^\Omega \) giving the confidence we can have in this proposition, without favoring one hypothesis contained in this proposition. The mass function \( m \) is defined as:

\[
m : 2^\Omega \rightarrow [0, 1] \\
A \mapsto m(A)
\]

and verify the properties:

\[
m(\emptyset) = 0 \quad \text{and} \quad \sum_{A \subseteq \Omega} m(A) = 1
\]

A mass distribution \( m_p \) on \( 2^\Omega \) is associated to each measured parameter \( p \). This distribution is defined by using fuzzy subsets in order to leave flexibility in the decision (Fig. 1). The subsets are defined following equations 6 for each value \( p \) of the parameter.

![Fig. 1. Mass functions definition.](image)

The fusion of several mass distribution \( m_p \) is fixed as follow: if the mass function associated with the first parameter \( p_1 \) is denoted by \( m_{p_1} \) and \( m_{p_2} \) for the second parameter \( p_2 \), and \( m_{p_1} \cap m_{p_2} \) is the mass function associated with the fusion of the two, the following relationship holds for all \( A \subseteq \Omega \):

\[
(m_{p_1} \cap m_{p_2})(A) = \sum_{B \cap C = A} m_{p_1}(B)m_{p_2}(C)
\]

B. Fusion scheme

In this paper, the fusion process uses the local statistical parameters presented in section II extracted from a SAS image. These parameters are fused following Fig. 2.

![Fig. 2. Detection method scheme.](image)

As seen on the scheme, the relationship between the two first statistical orders are kept by using the threshold in standard deviation and mean estimated by the automatic segmentation.
The choice of the thresholds $t_1$, $t_2$, $t_3$, and $t_4$ defining the mass functions (Fig. 1) are made considering the properties of these different parameters on SAS images and in order to limit the number of conflicts between sensors. These thresholds are obviously the same for all the sonar images. Concerning the standard deviation, the mass functions thresholds depend on the threshold evaluated by the standard deviation, the mean being tied to the standard deviation thanks to the proportional relationship due to the Weibull model (Eq. 2). But the same relationships defines the mass functions thresholds in function of the segmentation threshold.

IV. RESULTS AND EVALUATION

A. Mass functions definition

In order to highlight the interest of the detection method, this is tested on two different SAS images. The thresholds $t_1$, $t_2$, $t_3$, and $t_4$ (Fig. 1) are fixed according to the Tab. I.

<table>
<thead>
<tr>
<th>TABLE I</th>
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<tbody>
<tr>
<td><strong>THRESHOLDS FIXED FOR THE FUSION PROCESS (σₚ IS THE STANDARD DEVIATION THRESHOLD ESTIMATED BY THE AUTOMATIC SEGMENTATION).</strong></td>
</tr>
<tr>
<td></td>
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<tr>
<td>standard deviation</td>
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<td>skewness</td>
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<td>kurtosis</td>
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B. Results on real SAS data

The detection method described before is tested on a real SAS image. This image represents a region of 12m by 10m of the sea bed, with a resolution of about 10cm. On Fig. 3, a mine lies on the right (a) clearly visible, several buried mines (b, d, and e), a rock (c), and an unidentified object (f) barely visible, with a low signal to noise ratio. On Fig. 4, the image represents for each pixel the mass corresponding to the class “object”, high values (near 1) in the regions containing mines, and lower ones in the background. These mines seem to be well detected by the fusion process. Fig. 7 represents high values of “doubt” near the regions containing the sought objects and at the bottom of the image. The first remark comes from the imprecision on the limit between the echoes and the background. The second observation comes from the high level of noise in the region of the bottom. An image is then built associating to each pixel the class with the highest value of mass (Fig. 5). All the sought objects are well classified into “objects” except for the mine (e) classified into “doubt”. But some conflicts appear in spite of the choice of the mass function in order to limit it. However, this conflict, near “object” regions, could be easily removed by a markovian approach: if the “conflict” appears near an “object” region, it is considered as an “object” region.

If a parameter is removed from the fusion process (the skewness for example, Fig. 8), some changes appear (see the arrows). Indeed, the add of a parameter (the skewness) allows to classify some “doubt” regions into “object” (arrow in the middle) or “not object” (arrow at the bottom). But adding this parameter increases logically the conflict.

The last operation consists in applying the results of the fusion on the initial image: each pixel has its value weighted in function of the class it belongs to. For example, on Fig 6, the “object” pixels have been left to their original value, the “doubt” pixels have been weighted by a coefficient of 0.1, and the “not object” pixels by $10^{-2}$. The conflict region are left until now to their initial value. This process corresponds to an enhancing of the echoes, which is a response to the mine hunting experts who want to keep the structure of the initial sonar image (relief, structure of the echoes,…) to help them in their decision.

Similar results have been obtained on other SAS images [10].

C. Performance evaluation

In order to evaluate quantitatively the performance of the fusion process, two values are used. The first one comes from the non specificity [8] defined for a mass distribution $m$ as:

$$N(m) = \sum_{A \in \mathcal{U}} m(A) \log_2 |A|$$  \hspace{1cm} (8)

with $|A|$ the cardinality of the proposition $A$. In our case, the number of hypothesis being only two, the non specificity corresponds only to the mass of the proposition “doubt” $m(O \cup NO)$. From this formula comes a definition of the density of non specificity estimated on all the image:

$$d_{N(m)} = \frac{1}{N} \sum_{i=1}^{N} m_i(O \cup NO)$$  \hspace{1cm} (9)

with $N$ the number of pixels of the image and $m_i(O \cup NO)$ the mass of the proposition “doubt” after the fusion process for the pixel $i$. This value measures the quality of the fusion process on the specificity it gives in its result: the density is high if the fusion process does not give an accurate response ("object" or "not object") for many pixels of the image. Then lower is the density of non specificity, higher is the quality of the mass distributions and then the fusion process.

We derive in the same way a definition of the density of conflict defined as:

$$d_{C(m)} = \frac{1}{N} \sum_{i=1}^{N} m_i(\text{conflict})$$  \hspace{1cm} (10)

with $m_i(\text{conflict})$ the mass associated to the class “conflict” for the pixel $i$. Obviously, higher is this value, worse is the quality of the fusion process.

These values are estimated on the SAS image presented in the next subsection by using the results of the fusion of the different parameters (Tab. II).

We can make some remarks on the results. Firstly, the skewness and the kurtosis can give a less precise response ("object" or "not object") than the standard deviation (higher non specificity in the first case). Indeed, the mass distribution...
defined for the HOS give more place to the "doubt" than the mass distribution for the standard deviation. Secondly, the add of the skewness does not give more information in the fusion process (approximatively the same non specificity density with this parameter as without). But the add of this parameter increases slightly the conflict density.

These numerical results are confirmed by the visual observations on the fusion results obtained with the fusion of the different parameters (Fig. 5, 8 to 11). Indeed, the "doubt" regions obtained with the fusion of the skewness and the kurtosis are only larger than the corresponding regions obtained with the standard deviation only (compare Fig. 10 and 11). Moreover, the standard deviation parameter allows to identify as "object" the objects a, c, and f (Fig. 11), whereas the HOS parameters identify the objects a, b, c, and d (Fig. 10), and more precisely the skewness for the mine d. Then to conclude, all the parameters are useful for a good detection of approximatively all the sought objects, although the add of the skewness parameter gives less information than the others in the fusion process, but allows to consider the mine d as an "object" and not as a "doubt".

V. CONCLUSION AND PERSPECTIVES

The process proposed in this paper uses first, second, third, and fourth order local statistical properties of the SAS images giving parameters for a data fusion. This method based on the evidence theory, with fuzzy sets defining the mass distributions, allows to have a classification of each pixel of the image into "object", "not object" or "doubt". By this mean, we have a decision map with regions corresponding to each class and this map can be transposed on the original SAS image to highlight the regions of interest for an expert. This method is relatively simple and robust, and correctly classify even in the case of low signal to noise ratio (buried objects). Moreover, some values (non specificity and contrast densities) give to us an information of the interest of each fused parameter in the fusion process.

By this mean, it would be relatively easy to add other parameters (statistical or morphological) extracted from the SAS images by combining then to the results obtained with the fusion of the former ones. Moreover, we could evaluate the quantity of information bought by these new parameters and then estimate how interesting it is to add them in the fusion process.

**ACKNOWLEDGMENTS**

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**REFERENCES**


Fig. 3. SAS image (dB scale).

Fig. 4. Mass of the class "object".

Fig. 5. Result of the fusion of the three parameters: brown="object", yellow="doubt", bright blue="not object", dark blue=conflict.

Fig. 6. Enhancing of the echoes (dB scale).

Fig. 7. Mass of the class "doubt".

Fig. 8. Result of the fusion of standard deviation and kurtosis parameters only.
Fig. 9. Result of the fusion of standard deviation and skewness parameters only.

Fig. 10. Result of the fusion of skewness and kurtosis parameters only.

Fig. 11. Result of the "fusion" of standard deviation only.