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Arnaud Martin[1], Jean-Christophe Cexus[1], Gilles Le Chenadec[2], Elodie Cantéro[2], Thierry Landeau[2], Yann Dupas[3], Romain Courtis[4]

[1]E3I2, ENSIETA, 2 rue François Verny, 29200 Brest, France, {Arnaud.Martin,Jean-Christophe.Cexus}@ensieta.fr
[2]Alyotech Technologies, Rennes, France, {gilles.lechenadec,elodie.cantero,thierry.landeau}@alyotech.fr
[3]SHOM/DO/HOM/DEV, CS 92803 29228 Brest CEDEX 2, France, Yann.Dupas@shom.fr
[4]GESMA, DT/GESMA/GDM, CC42 - 29240 Brest Cedex 9, France, Romain.Courtis@dga.defense.gouv.fr

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New generations of autonomous underwater vehicle (AUV) allow new applications of submarine exploration. These AUV have a lot of sensors; several are devoted to environment assessment. The obtained data are both uncertain and imprecise due to the environment, to the sensors and also to the estimated position of the AUV. For a better rapid environment assessment we can use a maximum of the information given by the different kind of sensors.

Several problems must be dealt: how to modelize these imperfections, how to characterize the seabed, how to merge the information coming from different points of view and from different kind of sensors?

To solve these problems, we propose the use of the theory of belief functions. This theory allows taking into account the uncertainty and the imprecision of the data. We propose a framework to fuse the information coming first from different viewpoints of the same sensor and then from the results of different sensors: a side scan sonar, a sub bottom profiler, a bathymetric multibeam echo-sounder and a dual frequency single-beam echo-sounder.

1 Introduction

New generations of autonomous underwater vehicle (AUV) allow new applications of submarine exploration. These AUV have a lot of sensors devoted or not to environment assessment. The obtained data are both uncertain and imprecise due to the environment itself, to the sensors and also to the bad known position of the AUV. For a better and rapid environment assessment (REA) we can use a maximum of the information given by the different kind of sensors.

The main goal of the SHOM[1]- DGA[2] joint R&D program «Covert REA» is to prove the ability of AUVs to accurately and covertly describe the structure of the seafloor. In the frame of this program, the SHOM and the GESMA are working with a prototype, the DAURADE AUV, developed by ECA [1]. ALYOTECH TECHNOLOGIES and ENSIETA jointly carried out the development and linked studies of the data fusion of the DAURADE sensors in order to characterize insonified seafloors. The DAURADE sensors are a side scan sonar (SSS), a sub bottom profiler (SBP), a bathymetric multibeam echo-sounder (MBES) and a dual frequency single-beam echo-sounder (SBES). The different processing on these sensors and the uncertainty of the knowledge on the seabed lead to many imperfections on the data.

Therefore, we propose a generic data fusion to modelize these imperfections and to merge the information coming from different points of view and from the different kinds of sensors.

For this generic data fusion, we propose the use of the theory of belief functions. This theory allows taking into account the uncertainty and the imprecision of the data. We propose a framework to fuse the information coming first from different viewpoints of the same sensor and then from the results of different sensors.

The paper is organized as follow: first we describe the DAURADE AUV and the different sensors. We present the principle of the information fusion for multi-views and multi-sources fusion. Then, we show how the theory of belief functions can provide a solution for a generic data fusion.

2 The DAURADE AUV

The DAURADE AUV was developed by ECA [1]. For REA applications related to bottom and sub-bottom information, the DAURADE AUV carries four acoustical systems (Fig. 1): a Klein 5500 SSS, a Reson 7125 MBES, a Atlas DESO 35 SBES and a Edgetech 2200 SBP.

The figure 2 presents the sensors of the DAURADE AUV, information which can be extracted and processings allowing information to satisfy the input formalism of the proposed fusion tool. The data of each sensor are processed according their natures (acoustical or bathymetric) and their characteristics (emitted frequency, etc.) in order to extract a set of features, their associated position and the

[1] Service Hydrographique et Océanographique de la Marine
[2] Direction générale de l'armement

reliability of each sensor or processing. More details on sensor data processing are given in [2]. These features define four categories of information: the characteristics of sea sediment interface from the analysis (amplitude, statistics and/or textures) of the interaction between the acoustical wave and the seabed, the density of detected mine-like echoes (MILEC), the characteristics of the local bathymetry (slope, morphology, etc.), the characteristics within the first layers of sediment (layer thickness, absorption coeff., etc.).

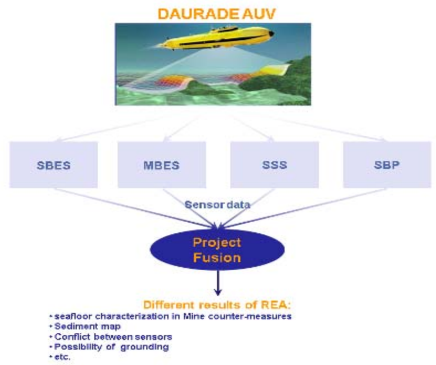

Fig.1 Definition of the fusion project data.

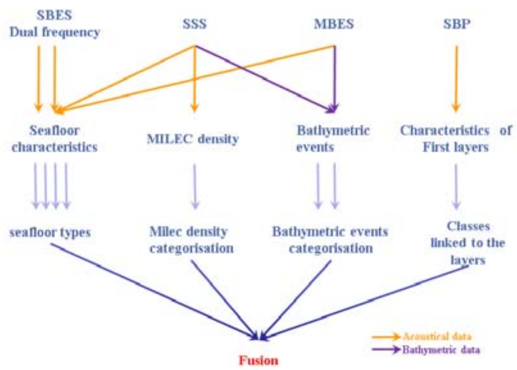

Fig.2 Data processing before the fusion stage.

3 Information fusion

The general principle of an information fusion approach is described in Figure 3. There are four steps of fusion: the modelization, the estimation, the combination and the decision. We can consider the information from different viewpoints of the same sensor to combine, as well as the information from different sensors looking the same area. But in fact the fusion process can be the same and seen as a fusion of classifiers.

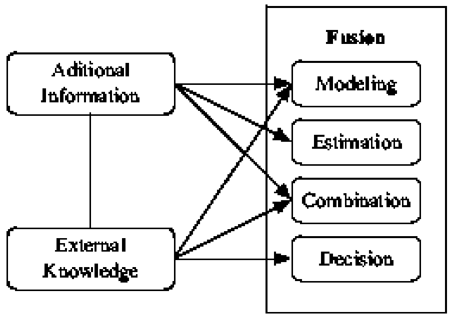

Fig.3 Information fusion flowchart.

For data fusion it is important to consider some external information such as the reliability of the source.

We can process the multi-views fusion and the multi-sensors fusion by the same method.

3.1 Multi-views fusion

The multi-view fusion is the combination of the different information from different point of view given by a same sensor. This can be seen as a classifier fusion and different approach can be used such as Bayesian method [3] or with the theory of belief function [4]. In [3,4] the fusion is applied on a side scan sonar but can be used also for other kind of sensor because the information coming from the different points of view are expressed by the same way. That is not the case for the multi-sensor fusion.

3.2 Tiling

Each sensor describes the seabed in its appropriate way, with different tiles. To fuse different sensors, first we must define the same part of the seabed to fuse. Therefore, we must define a homogeneous-size tile for each sensor.

For a given sensor, if the size of the tile for sensors fusion is bigger than the initial size of tile, we must fuse all the information in the biggest-size tile. This fusion of information coming from the same sensor can also be seen as a classifier fusion as presented in [5].

3.3 Multi-sensors fusion

The problem of the multi-sensor fusion is the difference of the frames of discernment, *i.e.* which kind of information each sensor can give.

The table 1 reports the frames of discernment (the set of information classes) which will be studied within the frame of the project. From the acoustical backscattered signals (BS) recorded by the SSS or MBES, the frame of discernment (silt, sand, sand/silt ripples, rock and vegetation) is expected to be reasonably predicted *via* an extraction of texture or statistical features. From the acoustical BS recorded by the SBES (in both low/ high frequency modes), the frame of discernment (silt, sand, rock and vegetation) will be studied. SBP BS will be exploited to predict the frame of discernment (hard/soft sediments) in which the acoustical wave emitted by the SBP hardly or not penetrates the insonified sediment. The two last frames of discernment deal with a particular processing of the SSS BS leading to the estimate of the mine-like echo (MILEC) density and the processing of bathymetric data of the MBES/SSS data in term of bathymetric events.

Sensors or processings	**Frame of discernment (Information classes)**
SSS BS	Silt Sand Sand\Silt ripples Rock Vegetation
MBES BS	Silt Sand Sand\Silt ripples Rock Vegetation
SBES BS (LF+HF)	Silt Sand Rock
SBP BS	Hard sediment Soft sediment
SSS BS	MILEC density
MBES/SSS Bathy	Bathymetric events

Table 1 Frames of discernment of each sensor

In a mine counter-measures scenario, a seafloor characterization has to be rapidly carried out. The outputs of the fusion stage for this scenario are imposed and are given in table 2. In this labelling scheme, a seafloor is defined by a letter A, B, C, D and a categorisation of the MILEC density. The letters A to C corresponds to a seafloor in which a mine can be buried or laid on the seafloor. The distinction between letters depends on an estimation of height variations (Δh) of the seafloor. A MILEC density categorisation (0-4) is added as extra information. The letter D corresponds to a seafloor on which mine counter-measures by sonar can not be possible. The reason of the impossibility is given by an extra letter among R (rocks), B (buried objects), V (vegetation: sea-grass or sea-weed), H (hole in the seafloor), Z (other).

A mapping between the frames of discernment (or information classes in Tab. 2) and the outputs of the fusion is necessary to make the multi-sensors fusion possible. Table 3 portrays this mapping for each information classes given by the different available sensors.

	Description		**Extra Information**	**MILEC Density (per square nautical mile)**
A	Ripples and possibility of buried objects	Δh <15cm	**0** : no information **1** : low density **2** : middle density **3** : high density **4** : very high density	**0** : unknown **1** : 0 - 20 **2** : 21 - 40 **3** : 41 - 70 **4** : > 70
B	Bathymetric variations and possibility of buried objects	15cm < Δh <30cm		
C	Bathymetric variation and possibility of buried objects Vegetation	60 > Δh >30cm		
D	Seabed making impossible to detect one-meter size object		**R** : Rocks **B** : possibility of buried objects **V** : Sea-grass/ sea-weed **H**: Hole **Z**: other	

Table 2 Outputs of fusion stage

	SSS / MBES BS	**SBES BS LF+HF**	**SBP BS**	**MBES Bathy**	**SSS MILEC Density**
A	Si,Sa,Ri	Si,Sa	Soft	Δh 0_15	1,2,3,4
B	Si,Sa,Ri	Si,Sa	Soft	Δh 15_30	1,2,3,4
C	Si,Sa,Ri,Ve	Si,Sa,Ve	Soft	Δh 30_60	1,2,3,4
DR	Ro	Ro	Hard		
DB	Si	Si	Soft		0
DV	Ve	Ve			0

Table 3 Correspondence between fusion outputs and information classes

For example, the A letter corresponds to:

- Information classes among silt, sand and ripple for the SSS or MBES data,
- Information classes among silt and sand for the SBES data,
- soft sediment predicted by the SBP data,
- A MBES bathymetric height variations Δh between 0 up to 15 cm.

The SSS MILEC Density categorisation provides to the letter A the extra information to form the final output labels.

4 Theory of belief functions

4.1 Theoretical background

The theory of belief functions allows for a representation of both imprecision and uncertainty through two functions: plausibility and belief [6]. Both functions are derived from a mass function defined by mapping of each subset of the space of discernment $\Theta=\{\theta_1, \ldots, \theta_n\}$ onto [0,1], such that:

$$\sum_{A \subseteq \Theta} m(A) = 1 \qquad (1)$$

where $m(.)$ represents the mass function.

When the reliability of the source is known, we can discount the mass function, transferring the belief on the ignorance:

$$\begin{cases} m^{\alpha}(A) = \alpha m(A) \\ m^{\alpha}(\Theta) = (1-\alpha) m(\Theta) \end{cases} \qquad (2)$$

The first step of the fusion process is the choice of the model. In [5], we use the model proposed by Appriou in [7] based on three axioms:

$$\begin{cases} m_j^i\left(\{\theta_i\}\right)(x) = \alpha_{ij} R_j p(q_j / \theta_i)/(1 + R_j p(q_j / \theta_i)) \\ m_j^i\left(\{\theta_i\}^c\right)(x) = \alpha_{ij} / (1 + R_j p(q_j / \theta_i)) \\ m_j^i(\Theta)(x) = 1 - \alpha_{ij} \end{cases} \qquad (3)$$

where q_j is the j^{th} classifier (supposed cognitively independent), $j=1,\ldots,m$, α_{ij} are reliability coefficients on each classifier j for each class $i=1,\ldots,n$ (in our application we can take $\alpha_{ij}=1$), and $R_j = (\max_{q_j,i}(p(q_j / \theta_i)))^{-1}$. Hence a mass function is defined for each classifier j and each class θ_i. In this approach, the difficulty is the estimation of the probabilities $p(q_j / \theta_i)$. In the case of decision level, θ_i is the class given by the classifier j. Hence the estimation of these probabilities can be made easily on a learning database using the confusion matrices: $p(q_j / \theta_i) = M_{ij}$, where (M_{ij}) is the confusion matrix.

If we do not have the confusion matrix of the sensor, we cannot apply the model given in (3). If we assume that we only have a global reliability α, we can define the mass function by:

$$\begin{cases} m(\theta_i) = \alpha \\ m(\Theta) = (1-\alpha) \end{cases} \qquad (4)$$

If we consider the numerical outputs of the classifiers, we can build the mass function as described in [8]. Another simple way is to normalize the outputs to get the normalization condition given by the equation (1) and then discount by the process given by the equation (2).

For the combination step, we can use many combination rules [9]. With the discounting process given by the equation (2), the conflict can be suppressed. This is the reason why we can use the initial normalized conjunctive rule of Dempster. The conjunctive rule is given for two sources by:

$$m_{\cap}(A) = \sum_{B \cap C = A} m_1(B) m_2(C) \qquad (5)$$

The Dempster rule is given by the normalization:

$$m_D(A) = \frac{1}{1 - m_{\cap}(\varnothing)} m_{\cap}(A) \qquad (6)$$

The mass on the empty set is generally considered as a conflict information. Therefore, we can keep this information in order to build a conflict map as shown in [4].

The last stage of the fusion process is the decision. In the evidence theory, we can use the maximum of plausibility, maximum of belief or maximum of pignistic probability [10]. We make a compromise by keeping the maximum of pignistic probability in this article.

4.2 Generic fusion based on the belief functions

Hence, we can have three uses of the generic fusion tool: the multi-view fusion, the tiling and the multi-sources fusion. For this three uses we can consider four actions:

1. the mass construction,
2. the discounting,
3. the combination
4. the decision.

In the case of multi-view fusion we have to build the mass functions (action 1) by one of the three ways proposed in the previous subsection (see equations (3), (4) and (5)) and then to combine (action 3) the mass functions given on the different views. We do not need to discount because we soon take into account of the reliability of the source in the mass functions process.

In the use of tiling, we have to combine (action 3) the different mass functions on a wanted-size tile and then, eventually, to decide (action 2) in order to obtain a map for each sensor.

For the multi-sources fusion, we first need to discount (action 2) the mass functions given by each sensor on the same tile. Then, we can combine (action 3) the mass functions of the different sensors together and decide (action 4) on the discernment frame of the final application.

5 Summary

The paper shows the possibility of a generic information fusion for a multi-sensors fusion, a tiling and a multi-sources fusion. The approach is based on the theory of the belief functions. This theory is interesting for this kind of generic tool because we can modelize the uncertainty and imprecision of the information and add the reliability of the sources.

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