The fusion of digital terrain models measured from multiple acoustic sensors – Application to the DAURADE autonomous underwater vehicle

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Abstract: *Building an accurate digital terrain model (DTM) of the seabed is a key issue for various military and civilian hydrographers applications.*
In the past decades, the emergence of autonomous underwater vehicles (AUV) offers new methodologies to collect the bathymetric data used in the estimation of the DTM. In our study, we use the DAURADE AUV platform which is capable of acquiring bathymetry with two acoustic sensors: A multibeam echo sounder (MBES) and an interferometric sidescan sonar (ISSS). The two sensors (MBES and ISSS) are synchronized to operate concurrently. In fact, the final DTM can be improved by performing a fusion of the data; the two systems acquire the bathymetry with different resolutions, geometries and error models; these parameters are introduced in the fusion process to improve the estimation of the DTM and to increase its accuracy.
The aim of this paper is to describe the fusion method and discuss our simulated results. First, the modeling of two acoustic sensors (MBES and ISSS) will be briefly described. The input data sets are simulated by applying the sensor models on simplified seabed models. The use of seabed models provides ground truth and, therefore, allows for quantifying the accuracy of the fusion process.

Keywords: *AUV, multibeam, interferometric sidescan, fusion, bathymetry, seafloor.*

1. Introduction

The most key issue of the international hydrographic community is the question of the irreducible uncertainty in modern surveys to build an accurate digital terrain model (DTM). As the base data for DTM estimation is a huge amount of noisy soundings, some automatic data-cleaning and DTM production package is recently developed such the Combined Uncertainty and Bathymetry Estimation (CUBE) [1] or the Cleaning through Hierarchic Adaptive and Robust Modelling (CHARM) [2]. These two algorithms are developed to process full coverage multibeam data when every sounding must include estimates of its uncertainty (CUBE case). Despite this is possible by using the quality factor proposed by [3], these algorithms can't integrates heterogeneous and qualitative data like expert opinion or bathymetry derived from *shape from shading* method. When many bathymetric data with different spatial resolution, coverage and uncertainty are available for the same area, the question arises whether this redundancy and complementary can be used to fuse them and generate a new DTM that is more wide and accurate.

In the past decades, the emergence of autonomous underwater vehicles AUVs which can be equipped with a wide variety of acoustic sensors or sonar systems, offers different methodologies to collect bathymetric data. In shallow water and for full coverage area survey, the two most used systems are multibeam echo sounder (MBES) and interferometric sidescan sonar (ISSS). The MBES still the standard sonar used for accurate hydrographic survey. But when installed on AUVs, which navigate usually close to the seafloor, it will suffer from its limited angular coverage and thus a lot of time consuming for full coverage which is difficult for vehicles with limited battery autonomy. In such survey conditions, there are advantages to use ISSS systems. An ISSS has a swath width of more than 10-times the altitude of the sonar and produce high resolution bathymetry across track. This would reduce significantly the time of the survey for full coverage. On the other hand, such system suffers from many disadvantages. The geometry of ISSS transducers doesn't allow gathering data in nadir area. It has a limited bathymetric accuracy about 2-3% of water depth. Another issue has been baseline decorrelation and the *shifting footprint effect* as described by Lurton [4]. In spite of these significant disadvantages, recent advantages in system electronics and algorithms have improved ISSS performance. In many AUV survey missions such as detecting and mapping submerged wrecks, rocks, and obstructions, the fuse of bathymetry derived from MBES and ISSS would improve productivity.

In this paper, we focus on MBES-ISSS bathymetric data fusion under uncertainty measurement. The remainder of this paper is organised as follows. Section 2 describes the bathymetric fusion model. Section 3 introduces the modeling of two acoustic sensors (MBES and ISSS) and the performance of the fusion model.

2. MBES-ISSS bathymetric data fusion model

Digital surfaces, derived from different sensors, contain intrinsic error due to acquisition and processing methodology in relations with terrain type and shape. In order to overcome limitations of each DTM, an intelligent fusion which consider uncertainty and reliability of each sensor is required. In radar community, the most used fusion algorithm to combine DTM's (SAR interferometry, LIDAR...) is a weighted average of inputs in each grid cell. As weights factor are not usually available, data accuracies are estimated from DTM (roughness, slope,...). To be robust to blunders, other methods are used by representing local patches as a sparse combination of basis patches [8].

These algorithms can't integrate prior knowledge about the precision and reliability of sensors which can vary with time and environment conditions. To deal with such kind of measurement, many theories have proved suitable for modeling uncertainty. We can mention imprecise probability, possibility theory and theory of belief function.

The theory of belief function, also known as Dempster-Shafer Theory (DST), was developed by Shafer [6] and initiated by the work of Dempster on imprecise probabilities. It's one of the popular approaches to handling uncertainty in literature for data fusion and it's often considered as a generalized model of probability and possibility theory. We will not introduce the basic of this theory. The interested reader can find sufficient interpretations of evidence theory in the literature.

In our case, inputs are soundings z_i with known position (x_i, yi) and standard deviation σ_i processed from MBS and ISSS and we look for more accurate z_i values by combining them. In [7] Petit-Renaud and Denoeux propose an evidential regression (EVREG) analysis of imprecise and uncertain data. In this model, evidential theory are extended to fuzzy sets where focal elements are fuzzy variables. The basic idea is to construct fuzzy belief assignment (FBA) in two steps: discounting FBA's m_i according to a measure of dissimilarity between inputs vectors, and combination of the discounted FBA's [7]. The model in our case may be summarized as follows.

Given a set of n sounding values $(y_i, z_i, \sigma_i, p_i)$ a FBA m_i can be defined for each pair (y_i, m_i) as:

$$\begin{aligned} m_i(F_i) &= p_i \\ m_i(Z) &= 1 - p_i \end{aligned} \tag{1}$$

Where F_i is a Gaussian fuzzy number with center z_i and standard deviation σ_i and reliability p_i of the sonar. Each element e_i of the inputs $I = \{e_i \,|e_i = (y_i, m_i), i = 1,2,\dots,n\}$ is a piece of evidence concerning the possible value of z_i, which can be represented by a FBA $m_z\,[y, e_i]$ as a discounting of m_i:

$$m_z\,[y, e_i] = \begin{cases} m_i(A)\varphi(\|y - y_i\|) & if\ A \in F(m_i)\backslash\{Z\} \\ 1 - \varphi(\|y - y_i\|) & if\ \ A = Z \\ \quad 0 & \text{otherwise} \end{cases} \tag{2}$$

Where $\varphi(.)$ is a decreasing function from $\mathbb{R}^+$ to $[0,1]$ verifying $\varphi(0) \in]0,1[$ and $\lim_{d\to\infty} \varphi(d) = 0$. $\varphi(.)$ represent a discounting function that measure the dissimilarity of the variable of interest z using a suitable metric $\|.\|$ between input vectors y and y_i. If y is close to y_i, $m_z\,[y, e_i]$ and m_i are very similar and vice versa. When the metric $\|.\|$ is defined as Euclidian distance, a natural choice for $\varphi(.)$ is [7]:

$$\varphi(d) = \gamma \exp(-d^2) \tag{3}$$

Where $\gamma \in]0,1[$ is a real parameter (usually taken $\gamma \in]0.95,1[$).

The information provided by each element of the input set can be combined by the conjunctive rule of Dempster. In practice we can neglect the effect of inputs y_i far from the position of interest y and only take k nearest neighbours. The final FBA is then:

$$m_z\,[y, I] = \cap_{i=1}^{k} m_z\,[y, e_i] \tag{4}$$

The presented EVREG model is applied for each sensor, and their outputs are combined using Dempster's rule to form a new FBA $m_i = m_i^{s1} \oplus m_i^{s2}$. The probabilistic density $BetP[y,I]$ associated to $m_z\ [y,I]$ exits, and has the following expression:

$$BetP[y,I](z) = \sum_{A \in F(m_z^*[y,I])} m_z^*[y,I](A) \frac{A(y)}{|A|} \quad (5)$$

Where $m_z^*[y,I]$ is the normalized version of $m_z\ [y,I]$ and $|A|$ is the cardinality of A.
For point prediction of the z value we can use the center of gravity of A (z_A^*). Then $\hat{z}$ can be expressed as:

$$\hat{z}(y) = \sum_{A \in F(m_z^*[y,I])} m_z^*[y,I](A)\ z_A^* \quad (6)$$

To measure the uncertainty involved in the prediction of FBA, we can used the *measure of nonspecifity* generalized for belief functions in [9]. This is defined as:

$$N(m_z\ [y,I]) = \sum_{A \in F(m_z\ [y,I])} m_z\ [y,I](A)\ \log_2|A| \quad (7)$$

3. Experiments

3.1 Simulated data

To validate our fusion process, we have developed a simulator for MBES and ISSS sonar. The simulator is based on construction of an adequate scattering-point model using a facet approach. In this approach, the synthetic bottom DTM is modeled as a set of triangular facets whose center represents the location of a scattering point and each facet has a unique identity composed of its normal vector, surface and its amplitude depending in sediment type. The signal received for each facet takes the form:

$$S_r(t) = A \sqcap_T e^{(j2\pi\nu_0\ (t-\tau_i))} D_e(\varphi) S_i BS_0(\theta) \frac{-2\alpha r_i}{r_i^2}$$

Where $S_e(t) = A \sqcap_T e^{(j2\pi\nu_0 t)}$ is the emitted signal, τ_i two way time propagation, $D_e(\varphi)$ the directivity of emission antenna, S_i triangular facet surface, $BS_0(\theta)$ is the backscattering strength depending on incident angle and sediment type, α is absorption coefficient and r_i is sonar facet distance.
A signal of 300 pings of a synthetic seafloor with three sediment types (flat mud, sand waves and rock) are collected with a MBES and ISSS with the following characteristics:

MBES
- 100 kHz system
- Beam aperture along-track 1°
- Beam aperture across-track 1°
- 64 transducer element

ISSS
- 100 kHz system
- Beam aperture along-track 1°
- Maximum range 75 m
- 3 receiving transducer with 25° depression angle

For the MBES the process consist of beamforming, depth detection by centre of gravity of the amplitude envelope and zero-phase difference instant estimation. For ISSS, the phase difference direction estimation is done by the so-called Vernier method using the three pairs of receivers. Next an outlier filter is applied to the estimated arrival angles. To estimate receive angle uncertainty, a 2nd degree polynomial is fit to each horizontal range bins of 30cm size and only one soundings is retained per bins. Sounding uncertainty of each sounding is estimated by using the quality factor proposed by Lurton et al. [3, 5]. It is the ratio between the estimated sounding and its standard deviation obtained from signal characteristics

3.2 results

The estimated soundings data for both systems is collected, using the simulator described above, throw three survey lines. Line in position y=0 is surveyed with both systems and the two other only with MBES (see 'FIG.1').

Figure '*Fig.2'* displays the results obtained for three scenarios data fusion: ISSS alone, ISSS and MBES survey line at y=0, ISSS line at y=0 and three MBES lines at y=0, 60 and -60. The pignistic probability distribution, also the width of first and ninth deciles interval, can be seen to reflect the uncertainty taking into account both the scatter and the density of input soundings. The uncertainty is maximal in the extremity of the profile in all scenarios because there is no input data. It's also maximal for the two first cases in the -67 range because of shadows in ISSS data. This effect can be also detected on the nonspecificity measurement. The nonspecificity measurement shows the contribution of the fusion of the MBES and ISSS data by the decreasing of uncertainty in overlapping ranges.

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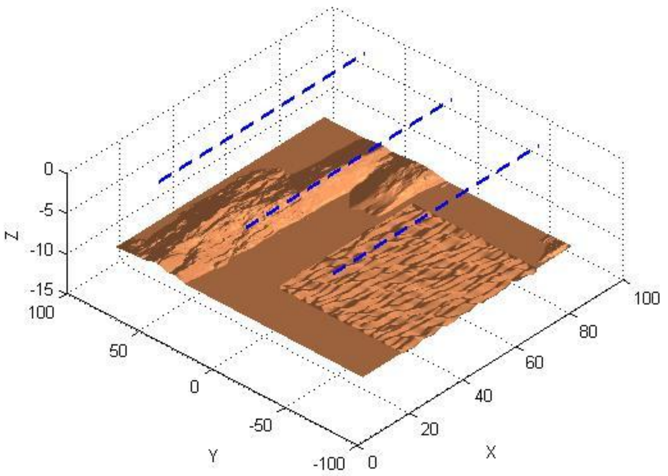

Fig.1: Simulated sea bottom and survey lines (broken lines).

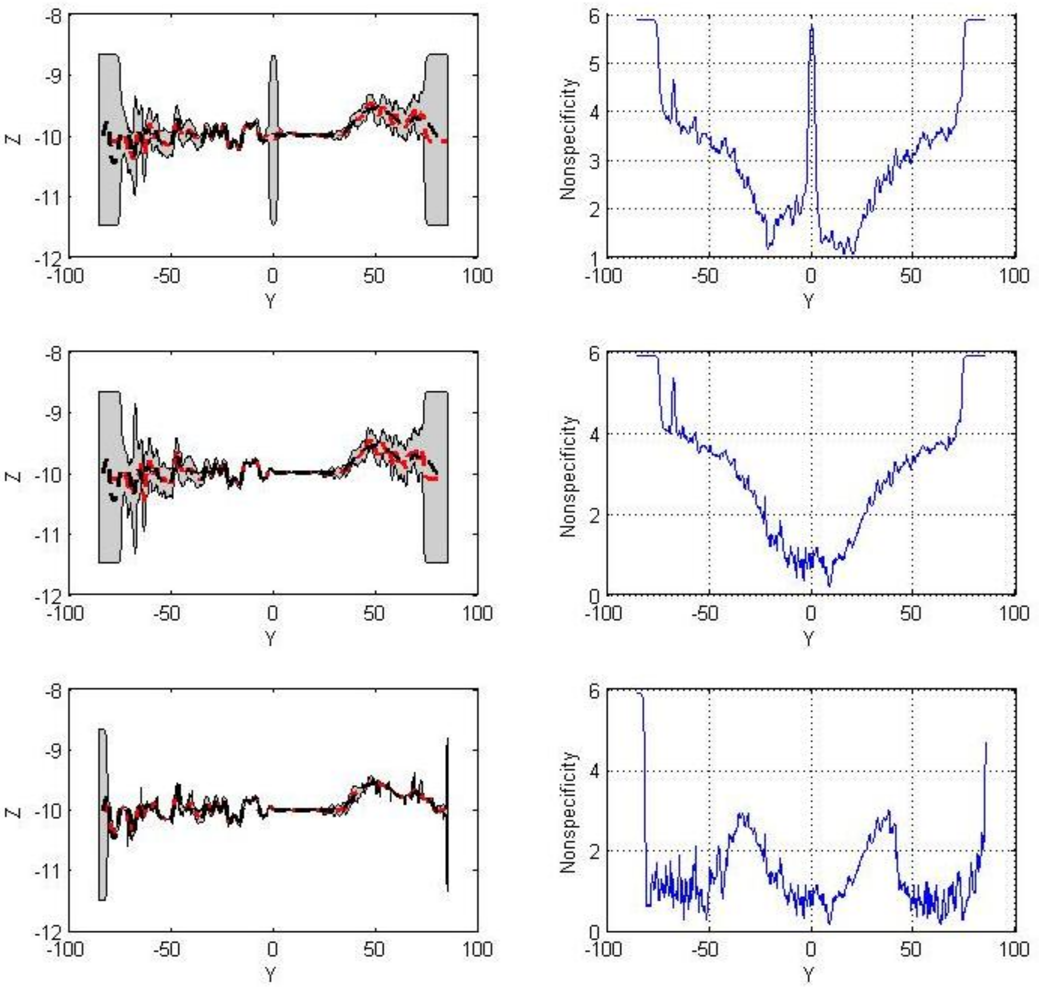

Fig.2: One ping fusion result for three scenarios. Left figures shows the estimated depth at the same resolution of the ISSS (red broken lines) with the actual depth (black broken lines) and first and ninth deciles of the pignistic distribution (grey area). Right correspondent nonspecificity measurment