Swath bathymetric data fusion Application to autonomous underwater vehicles

Ridha Fezzani*, Benoit Zerr*, Michel Legris*, Ali Mansour* and Yann Dupas†
*Lab-STICC UMR CNRS 6285 ENSTA Bretagne
2 rue François Verny, 29806 Brest Cedex 9, France.
Email:ridha.fezzani@ensta-bretagne.org ; benoit.zerr@ensta-bretagne.fr;
michel.legris@ensta-bretagne.fr; mansour@ieee.org
†SHOM/DOPS/HOM/DEV
13 rue du Chatellier CS 92803, 29228 BREST Cedex 2, France.
Email: yann.dupas@shom.fr

***Abstract*—The autonomous underwater vehicle (AUV) DAURADE platform can acquire bathymetry with two acoustic sensors: a multibeam echo sounder (MBES) and an interferometric sidescan sonar (ISSS). The two sensors (MBES and ISSS) are synchronized and they can simultaneously operate and acquire the bathymetry with different resolutions, geometries and error models. This complementarily allows us to improve the accuracy and the coverage of the collected bathymetric data by fusing both of them. We applied the fusion process on actual data from the two bathymetric sensors of DAURADE (Reson 7125 MBES and Klein 5000 Interferometric); the obtained results are presented and discussed.**

I. Introduction

A major issue for the international hydrographic community is how to build an accurate digital terrain model (DTM) knowing the irreducible uncertainties in modern surveys. In fact, DTM estimation requires a huge amount of soundings which are usually noisy. Various automatic data-cleaning systems and DTM production package have been recently developed using the Combined Uncertainty and Bathymetry Estimation (CUBE) [1] or the Cleaning through Hierarchic Adaptive and Robust Modeling (CHARM) [2]. The latter two algorithms are implemented in order to process full coverage multibeam data in which every sounding should include an estimation of its uncertainty (CUBE case). This requirement is achievable using the quality factor in [3]. However CUBE and CHARM algorithms can not integrate heterogeneous and qualitative data as it can be done by an expert. When many bathymetric data with different spatial resolutions, coverage and uncertainties are available for the same area, a question arises out of this problem: can this redundancy and complementarities be used to generate more accurate DTM? In the last decade, autonomous underwater vehicles (AUV), equipped with a wide variety of acoustic sensors or sonar systems, have been deployed to collect bathymetric data. In shallow water and for full coverage area survey, the two most used systems are the multibeam echo sounder (MBES) and the interferometric sidescan sonar (ISSS). The MBES is considered as the reference system for an accurate hydrographic survey. Unfortunately MBES on AUV navigating close to the seafloor suffers from its limited angular coverage. With such limitation, a full coverage is time consuming and not compatible with the battery autonomy. Therefore ISSS can advantageously be used in this case. An ISSS has a swath width over 10-times the altitude of the sonar and produce high resolution bathymetry across track. The latter propriety helps significantly reducing the time of the survey for a full coverage. On the other hand, such system suffers from many drawbacks: The geometry of ISSS transducers does not allow gathering data in nadir area, it has a limited bathymetric accuracy about 2-3% of water depth, and it is penalized by the baseline decorrelation and the shifting footprint effect. In spite of these significant disadvantages, recent developments in system electronics and processing 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 can improve the productivity.

This paper is organized as follows: Section II describes the fusion model of bathymetric data, AUV DAURADE and the two swath bathymetric sonars are presented in section III, and section VI discusses the results.

II. BATHYMETRIC DATA FUSION PROCEDURE

In radar community, the most used fusion algorithm to combine DTMs (SAR interferometry, LIDAR, *etc.*) is a weighted average of inputs in each grid cell. As the weight factors are not usually available, data accuracies are estimated from DTM (roughness, slope, etc...). To be robust against blunders, other methods are used by representing local patches as a sparse combination of basis patches [4]. These algorithms can not integrate a prior knowledge about the precision and reliability of sensors which can vary with time and environment conditions. In order to overcome limitations of each DTM, an intelligent fusion which considers uncertainty and reliability of each sensor becomes necessary.

To deal with such kind of measurement, many theories have been proved suitable for modelling the uncertainty. It is worth mentionning that imprecise probability, possibility theory and theory of belief functions are widely used in the literature.

The theory of belief functions, also known as Dempster-Shafer Theory (DST), was developed by Shafer [5] and initiated by the work of Dempster on imprecise probabilities. Actually, it is one of popular approaches to handle uncertainty in literature for data fusion and it is often considered as a generalized model of the probability and possibility theory. The basic of this theory is omitted in this manuscript. Interested readers can find sufficient interpretations of evidence theory in the literature ([6], [7]).

A. Fusion model

In our application, inputs are the sounding z_i with a known position y_i and a standard deviation σ_i obtained from MBS and ISSS. We are aiming to improve the accuracy of z_i values by combining the outputs of the sonars. In [8], Petit-Renaud and Denoeux propose an evidential regression (EVREG) analysis of imprecise and uncertain data. In their model, evidential theory are extended to fuzzy sets where focal elements are fuzzy variables. The basic idea is to construct a fuzzy belief assignment (FBA) in two steps: discounting FBAs mi according to a measure of dissimilarity among input vectors, and the combination of a discounted FBAs [8]. 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 a mean z_i and a standard deviation σ_i and p_i stand for the reliability of the sonar. Each input element e_i ($I = \{e_i | e_i = (y_i, m_i), i = 1, 2, ..., n\}$) is a piece of evidence concerning the possible value of z_i in a given position y, which can be represented by a FBA $m_z[y, e_i]$ as a discounting of m_i:

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

where $\varphi(.)$ is a decreasing function from $R^+ \to [0, 1]$ satisfying that $\varphi(0) \in]0, 1[$ and $\lim_{d \to +\infty} \varphi(d) = 0$. $\varphi(.)$ can be considered as a discounting function that measures 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 become very similar to each other and vice versa. When the metric $\|.\|$ is defined as the euclidian distance, an evident choice for $\varphi(.)$ becomes [8]:

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

where $\gamma \in]0, 1[$ (usually $\gamma \in]0.9, 1[$). The information provided by each element of the input set can be combined by the conjunctive rule of Dempster. In practice, the effect of inputs y_i far from the position of interest y can be neglected and we should consider only k nearest neighbors. The final FBA becomes:

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

The presented EVREG model is applied for each sensor, and its outputs are combined using Dempsters rule to form a new FBA $m_i = m_i^{s_1} \oplus m_i^{s_2}$. The probabilistic density $BetP[y, I]$ (named pignistic probability function) associated to $m_z[y, I]$ has the following expression:

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

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

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

The uncertainty involved in the prediction of FBA can be calculated using the *measure of nonspecifity* generalized for belief functions [9] which is defined as:

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

The *measure of nonspecifity* represents our inability to distinguish true from false possible alternatives.

B. Measurement of sounding uncertainty

Recently, a new quality factor was proposed by Lurton *et al.* in [3] and [10] to measure the bathymetric uncertainty of each sounding directly on the received sonar signal. This factor represents the ratio between the estimated sounding and its standard deviation obtained from signal characteristics. In case of MBES, the quality factor depends on the detection algorithm applied to the complex signal. When the amplitude signal is processed using a centre of gravity approach, the uncertainty is measured as in [10]:

$$q_A = \frac{\sqrt{12}}{B\sqrt{\frac{4}{\pi} - 1}} \frac{t_D}{\sqrt{N} T_{eff}} \tag{8}$$

where t_D is the estimated detection instant, N is the number of independent time samples, B is a factor depending on the envelope shape and T_{eff} is twice the second order moment of the envelope.
For zero-phase difference instant estimation, the uncertainty is defined by [10] as:

$$q_\phi = \frac{\alpha t_D}{\delta \Delta \phi} \frac{1}{\sqrt{\frac{(t_D - \bar{t})^2}{\sum_{i=1}^{N} (t_i - \bar{t})^2} + \frac{1}{\frac{N}{N_p}}}} \tag{9}$$

Where α is the phase ramp slope, $\delta \Delta \phi$ is the phase standard deviation and Np is the number of samples in transmitted signal.
$\delta \Delta \phi$ can be computed from the variations of the actual phase values around the ideal fitted curve.

In the case of ISSS processing, phase difference fluctuations cause uncertainty in sounding detection as [3]:

$$q_{F\phi} = \frac{1}{\tan\theta\sqrt{(\frac{\lambda}{2\pi\cos\gamma}\delta\Delta\phi)^2 + (\frac{cT\cos^2\theta}{2H\sqrt{12}\sin\theta})^2}} \quad (10)$$

where a is the interferometer baseline, λ stands for the wavelength, γ is the angle of arrival referenced to baseline axis, the arrival angle is θ, T is the signal duration and H represents the depth. The phase-difference standard deviation $\delta\Delta\phi$ can be estimated in similar way to zero-phase difference instant processing over a time interval around the detection instant.
These quality factors were tested on simulated and actual data and they provide a promising perspective.

III. DATA AND SONAR DESCRIPTION

A. AUV Daurade

The Daurade vehicle was built by ECA Company for the benefit of the French hydrographic and oceanographic service (SHOM) and the Atlantic undersea studies group (GESMA). It is a multi-purpose experimental AUV for Rapid Environment Assessment (REA), which is a military concept to acquire and transmit rapidly environment data on a poorly known area. The vehicle is 5m length and has 10 hours autonomy at 4 knots. It contains a PHINS Inertial Navigation System, GPS receiver and Doppler Velocity Log which improves navigation accuracy and extends full autonomous operation. Daurade also comes with a navigation post-processing system (DELPH INS), which can be applied to increase the navigational integrity and to maximize the position accuracy using GPS surface fix.

B. Swath bathymetric sonars

The DAURADE carries a multibeam echosounder and an interferometric synthetic aperture sonar both mapping sensors. The multibeam echosounder is a SeaBat 7125-AUV characterized by: 512 beams of width $0.5° \times 1°$; a total aperture of $128°$; a frequency of transducer 400 kHz; equidistant beams; 300 m max range; depth resolution 5 mm. The interferometric sidescan sonar is a Klein series 5500, a frequency of transducer 455 kHz, baseline spacing 6.5 wavelengths, 75m-150m range.

C. Data processing methods

The study area is located near the west coast of France, in the harbor of Brest. The water depth of the area ranges from 19 to 34 meters. The seabed presents a slope in the south to north direction. Two survey lines spacing of 115m were used. This provided a light degree of overlapped data for the interferometric sonar and no overlapping for MBS soundings. The AUV depth was maintained to 7m during the survey which is not appropriate for our study to show the disadvantage of the MBS when operating in shallow water. The area covered by the two ISSS lines is about 260 by 135 meters.

For the survey the klein 5500 was run on a range scale of 75m per channel (the other range scales are very noisy). Bathymetric data is measured using the so-called Vernier Method which consists of estimating a unique receiving angle by combining pairs of stave measurements ([11], [12]). The standard deviation of each sounding is estimated according to (10). The final soundings were de-spiked for gross outliers and down sampled to one sounding each 20 cm across track distance to reduce the huge amount of data (2276 per channel per ping). Bathymetric soundings from MBS are calculated from the raw formed beam data using a center of gravity approach for the amplitude data and a zero-phase difference instant estimation for the phase difference data. The standard deviation of each sounding is estimated according to (8) and (9). Sounding with better quality factor was maintained for each ping.

The sound speed profile was not available so data wasn't corrected for the water column refraction which affected the horizontal and vertical positions of soundings for both systems, specially the ISSS with more grazing angles. For purpose of MBS-ISSS bathymetry fusion, we gridded the area covered by ISSS. Gridding was carried out to a 0.2 meter pixel resolution. Following gridding, 5 nearest neighbors soundings from each sonar were employed to estimate the fused sounding. Reliability pi is set to 1, so only sounding uncertainty is used in fusion process.

IV. EXPERIMENTAL RESULTS

Fig.1 and Fig.2 present the bathymetric data which should be fused. A blind zone can be observed on the nadir of the ISSS bathymetry and the noisy outer beams. MBS bathymetry has a gap in southern line due a malfunction of the sonar when recording raw formed beam data. Notice that bathymetric data aren't smoothed to not bias the estimated standard deviation.
Fig.3 presents outcomes of our algorithm i.e the obtained bathymetry. Some parts of the image are noisy because of the residual outliers of ISSS data, uncorrected bathymetry with water column celerity profile and the AUV drift which is not perfectly corrected by DELPH INS software.

to have an idea about the quality of the fused bathymetry, Fig.4 and Fig.5 show respectively the measure of nonspecificity and the first to the ninth deciles of the pignistic probability interval. As expected, the area covered by the MBS data was more precise than the other. This is clearly identifiable on a cross profile (south to north) of a single grid line of the measure of the nonspecificity (Fig.6) which expresses the uncertainty of the fused bathymetry.
Fig.7 presents the estimated depth along a cross profile and the 0.1 and 0.9 quantiles of the pignistic probability, as a confident interval. In Fig.6, we can notice that the presence of MBS data makes the confident interval very narrow. We can notice also, the *bow tie* effect of the end of across swath due to the noisy outer beams of the interferometric sidescan sonar.

As with all interferometric systems, when the slopes on the seabed reach certain stage, the phase calculation begins to fail. This is the case of ISSS data on Fig.5 for the northern line, where the confident interval is wider than the other line without slope.

V. CONCLUSION

In this manuscript, bathymetric data fusion using belief function has been described. This approach allows us to

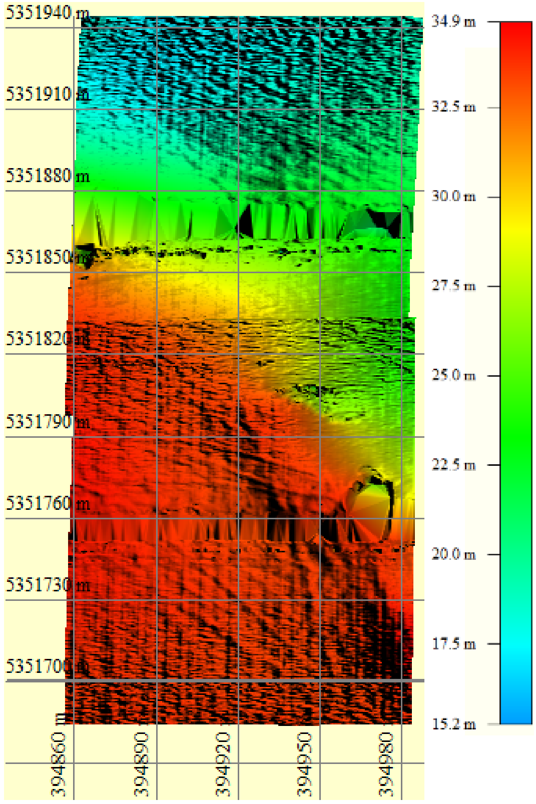

Fig. 1. Gridded Klein 5500 bathymetry on two parallel lines.

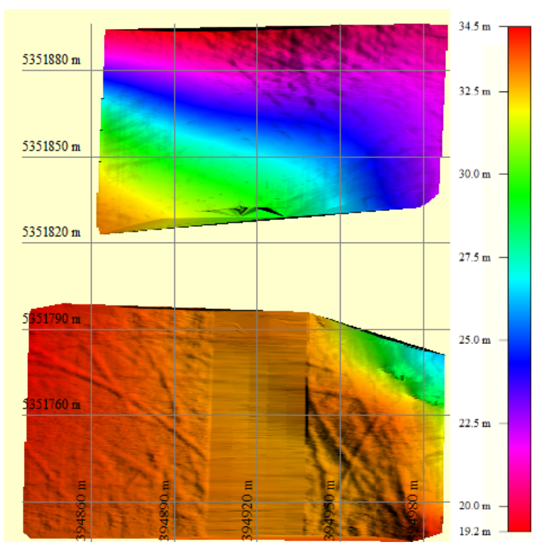

Fig. 2. Gridded Reson 7125 bathymetry on two parallel lines.

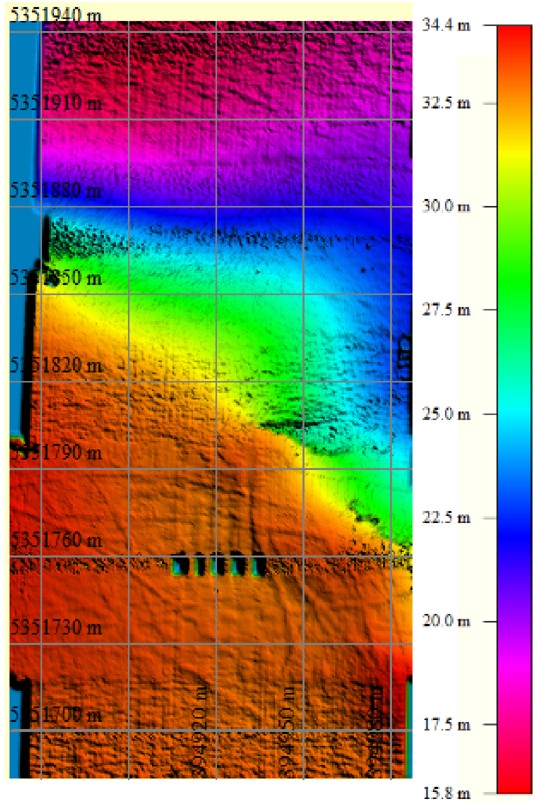

Fig. 3. Gridded bathymetry after fusion.

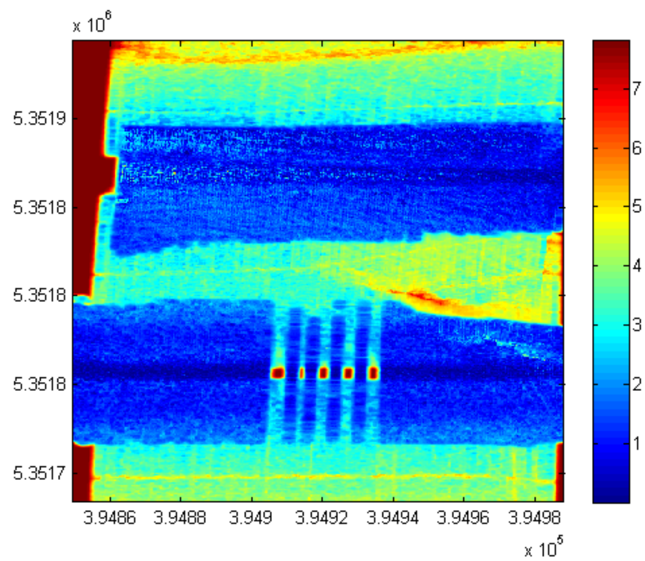

Fig. 4. The measurement of nonspecificity of fused bathymetry.

integrate the precision and the reliability of source data. The targeted estimator of the bathymetry error associated with every sounding involved in the fusion process should gives an objective quality of the fused bathymetry.

In spite of the difficult steady area and the use of data not corrected with water column celerity profile, the fusion method allows us to obtain a bathymetric data with quality factors very useful for Rapid Environment Assessment(REA). The fusion process depends on AUV navigation (horizontal position) and all common sounding corrections. Our future work consists in applying the fusion process to a corrected bathymetric data on a flat seabed and to define an optimum adaptive survey using the fused bathymetric quality.

Acknowledgment

The authors would like to express their gratitude to A. Bertholom (Atlantic undersea studies group) for providing the DAURADE data presented in this work.

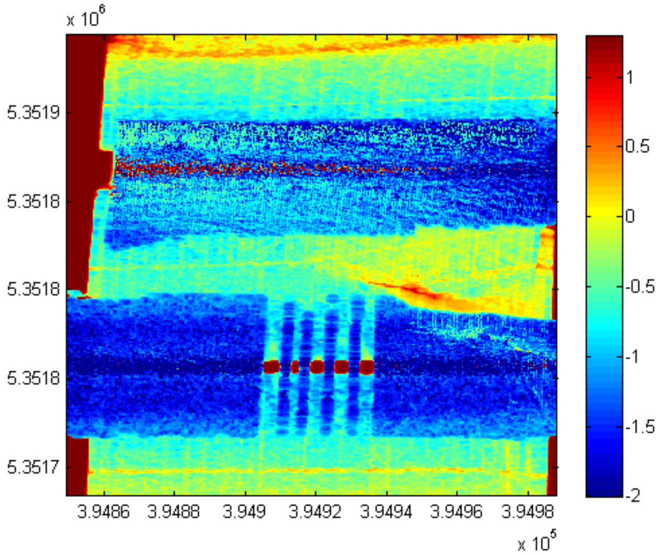

Fig. 5. The difference between 0.9 and 0.1 quantiles of pignistic probability on log scale.

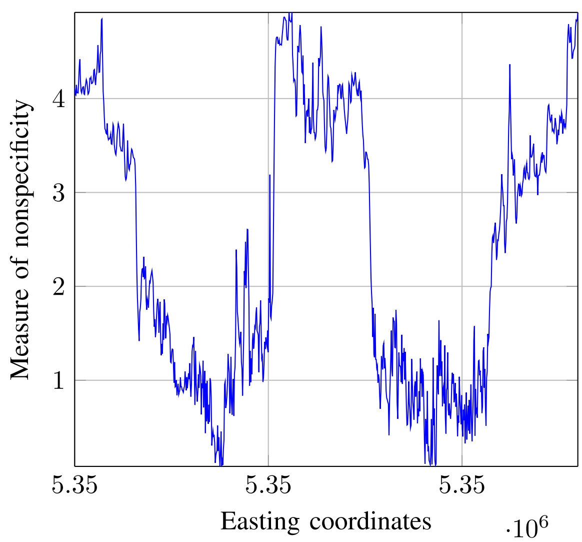

Fig. 6. A cross profile of a single grid line

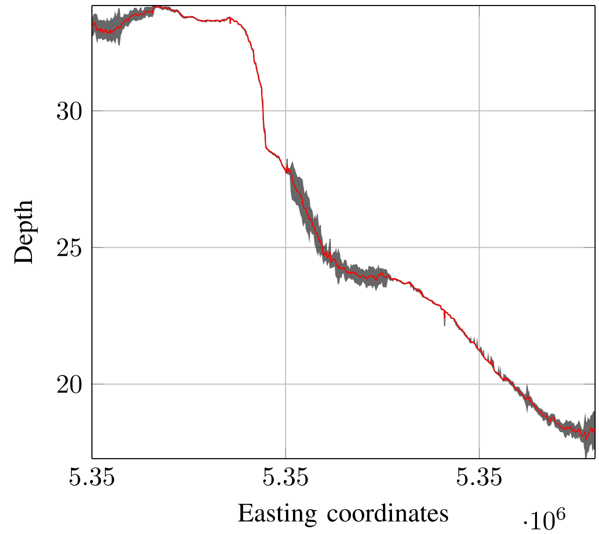

Fig. 7. A cross profile of a single grid line. First and ninth deciles of the pignistic probability (grey area). Estimated depth(red line)

REFERENCES

[1] B. R. Calder and L. A. Mayer, "Automatic processing of high-rate, high-density multibeam echosounder data," *Geochemistry, Geophysics, Geosystems*, vol. 4, no. 6, pp. n/a–n/a, 2003. [Online]. Available: http://dx.doi.org/10.1029/2002GC000486

[2] N. Debese, R. Moitié, and N. Seube, "Multibeam echosounder data cleaning through a hierarchic adaptive and robust local surfacing," *Computers & Geosciences*, vol. 46, pp. 330–339, 2012.

[3] X. Lurton and J. Augustin, "A measurement quality factor for swath bathymetry sounders," *IEEE Journal of Oceanic Engineering*, vol. 35, no. 4, pp. 852–862, Oct. 2010.

[4] H. Papasaika, E. Kokiopoulou, E. Baltsavias, K. Schindler, and D. Kressner, "Fusion of digital elevation models using sparse representations," in *Photogrammetric Image Analysis*, ser. Lecture Notes in Computer Science, U. Stilla, F. Rottensteiner, H. Mayer, B. Jutzi, and M. Butenuth, Eds. Springer Berlin Heidelberg, Jan. 2011, no. 6952, pp. 171–184.

[5] G. Shafer *et al.*, *A mathematical theory of evidence*. Princeton university press Princeton, 1976, vol. 1.

[6] R. R. Yager and L. Liu, *Classic works of the Dempster-Shafer theory of belief functions*. Springer Science & Business Media, 2008, vol. 219.

[7] B. Khaleghi, A. Khamis, F. O. Karray, and S. N. Razavi, "Multisensor data fusion: A review of the state-of-the-art," *Information Fusion*, vol. 14, no. 1, pp. 28–44, 2013.

[8] S. Petit-Renaud and T. Denoeux, "Nonparametric regression analysis of uncertain and imprecise data using belief functions," *International Journal of Approximate Reasoning*, vol. 35, no. 1, pp. 1–28, Jan. 2004. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0888613X03000562

[9] D. Dubois and H. Prade, "A note on measures of specificity for fuzzy sets," *International Journal of General Systems*, vol. 10, no. 4, pp. 279–283, Feb. 1985. [Online]. Available: http://dx.doi.org/10.1080/03081078508934893

[10] Y. Ladroit, X. Lurton, C. Sintes, J. Augustin, and R. Garello, "Definition and application of a quality estimator for multibeam echosounders," in *OCEANS, 2012 - Yeosu*, May 2012, pp. 1–7.

[11] G. Llort Pujol and C. Sintes, "Vernier interferometer performance analysis," in *Oceans'11 MTS/IEEE Kona*, Kona, United States, Sep. 2011, p. . [Online]. Available: https://hal.archives-ouvertes.fr/hal-00632761

[12] B. Zerr, S. Goanvic, B. Breton, and C. Genty, "Bathymetric sidescan sonar : a system dedicated to rapid environment assessment," in *Oceans 2005 - Europe*, vol. 1, June 2005, pp. 118–123 Vol. 1.