Automatic Processing of Bathymetric Data from Multibeam Echosounders

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Brian Calder, Center for Coastal and Ocean Mapping/Joint Hydrographic Center,
University of New Hampshire, Durham NH 03824

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Draft of Vessel
Dynamic Draft
Tides

Error Assignment
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Background

Multibeam Echosounder data is a powerful method for rapidly mapping the seabed, either from the water surface or from a remote (or autonomous) vehicle. However, the data rate of such systems can make data handling difficult, and most conventional processing schemes rely on subjective decisions.

This poster describes an automatic scheme for converting raw data to a preliminary gridded product without human interaction, using the estimated measurement error of the data to adjudge the reliability of each sounding and hence the weight that it should be given in the grid. At each point of interest, the location of which is assumed perfectly known, we track an estimate of depth and the uncertainty in that depth estimate constructed from the measured depths and estimated measurement errors in the area around the grid node. Hence, we call this algorithm CUBE (Concurrent Uncertainty and Bathymetry Estimator).

In the ideal case, each specific point on the surface should be defined with exactly one "true" depth. However, with data errors and echosounder failure modes, there are often outliers in the data stream that must be addressed by any practical algorithm. To provide the required extra robustness, our algorithm is able to track multiple estimates of depth, starting a new track if the data being presented for assimilation appears to be inconsistent with any current tracks. All tracks are maintained on-line in a simple flat database; at any time, CUBE can extract the "current best" estimate for depth and uncertainty and construct a surface from the estimates extracted in a given area.

The flow-path for data assimilation and surface construction is outlined above, and described in the boxes below. We illustrate the algorithm components and the problems associated with data outliers, with examples drawn from multibeam datasets in Portsmouth, NH and the eastern Gulf of Mexico shelf. Our examples show that the algorithm provides results equivalent to human hand-edited data, but without the associated subjectivity.

Error Assignment

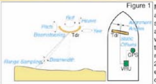

Figure 1

Measurement errors are a function of basic acoustics, the offsets between components of the survey system and the accuracy with which these are measured and compensated (Figure 1), as well as the accuracy of the auxilliary sensors used to measure vessel attitude etc. For each sounding recorded, an estimate is made of vertical (Figure 2) and horizontal (Figure 3) error. These error estimates are valid as long as the echosounder is operating properly, which we assume at this stage.

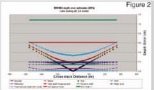

Figure 2

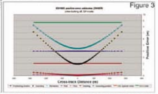

Figure 3

Error model data courtesy of Rob Hare. Ref.: "Accuracy Estimation of Canadian Swath (Multi-Beam) and Sweep (Multi-Transducer) Sounding Systems", R. Hare, A. Godin and L. Mayer, CHS Tech. Report, 1995. Error values are illustrative of a specific configuration of vessel, auxiliary sensors and environmental conditions (EM1000 in CA shallow mode at 60m depth) and are not an exhaustive summary of performance.

Data Assimilation

A zero-order prediction of depth (figure 4) is used to project data from measurement location to estimation node, diluting certainty as a function of distance projected.

Under an assumption of Normality, an optimal assimilation is the Bayesian update (figure 5), where we track only the mean and variance of the posterior distribution (sufficient for a Normal variate). We treat data at a node as a pseudo-time sequence (figure 6) and recursively update our estimate of depth and uncertainty to track the input data as it arrives. This minimises memory and computation overheads.

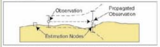

Figure 4: Zero-order prediction of depth (i.e., the sea-floor is locally flat). Uncertainty increases with distance from measurement to estimation location.

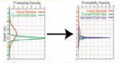

Figure 5: Bayesian update for current estimate and new data. Only mean and variance are tracked.

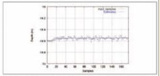

Figure 6: New estimates are assimilated recursively, using the model of a pseudo-time sequence.

Ref.: 'Bayesian Forecasting and Dynamic Models', M. West & J. Harrison, 2 ed., Springer-Verlag, 1997

Robustness

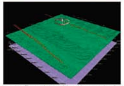

Figure 7: Raw data with along-track shoaler outliers. Data points colored by depth, scaled according to expected (1σ) vertical error.

When outliers appear, evidence of multiple depths may be presented (Figure 7). To compensate, we extend the model to be piecewise defined, starting a new depth hypothesis track if the input data is unlike any existing hypothesis (Figure 8). Similarity is determined by Bayes factors for the best current track against an alternate with a step shoal, and model monitoring is implemented via sequential Bayes factor analysis. This simple extension makes the tracking significantly more robust as outliers are collected into secondary hypotheses (Figure 9), leaving the primary "true" depth hypothesis uncorrupted.

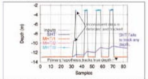

Figure 8: Single/Multiple-Hypothesis tracking from same area as figure 7. SHT is single hypothesis; MHT/x is multiple hypothesis x.

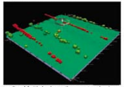

Figure 9: Multiple hypotheses tracked, scaled according to composite uncertainty. Secondary hypotheses are much less certain.

Disambiguation

Disambiguation is the process of deciding which of the tracked depth hypotheses is "best". Given burst-mode failures (Figure 10), many hypotheses may be present (Figure 11). The simplest alternative is to report the hypothesis held longest (most data integrated), Figure 12. However, this may not be effective in very noisy data, as here (Figure 13). An alternative is to find the nearest single hypothesis (hence certain) node, and select the hypothesis closest to this depth; the addition of spatial context significantly improves the reconstruction robustness (Figure 14). In all cases, the reconstruction must be considered in terms of the number of hypotheses (Figure 15) when making decisions on final depths.

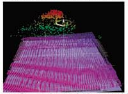

Figure 10: Raw data in area of echosounder failure. Multiple passes provide data to define surface.

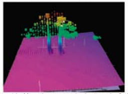

Figure 11: Hypotheses tracked at end of data. Note 'best' surface eliminates most noise data.

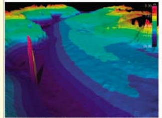

Figure 12: Reconstruction with longest held hypothesis, view from NNW. Failure still evident.

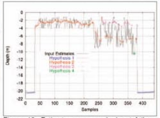

Figure 13: Estimate sequence in burst failure. More data is in error than correct, hence difficulties.

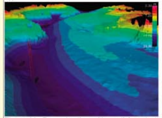

Figure 14: Reconstruction with spatial context, viewed from NNW. Compare figure 12.

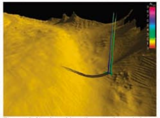

Figure 15: Number of hypotheses color-coded over bathymetry from figure 14, view from south-west.

Comparison Study

To compare traditional and automatic processing, we use a section of a survey collected in the eastern Gulf of Mexico during September 2001 with a Simrad EM1002. The raw data-set was corrected to Mean Lower Low Water (MLLW) with predicted tides. The data stream was hand-edited during the survey, and was then processed by CUBE with and without reference to these hand-edits so that we are not comparing different gridding systems as well as the automatic processing. The resulting surfaces (e.g., figure 16) are good representations of the data.

A node-wise comparison of the surfaces (figures 17-18) shows no significant difference between the hand-edited data and the automatically processed data. IHO vertical specifications for Order 2 survey are a 95% confidence limit of 1.70m at 60m (range here is 60-120m); these results are significantly better. CUBE's robustness is well illustrated by comparing the surface constructed with raw data (figure 19) and in areas of small detail (figure 20).

CUBE also provides auxilliary information, such as where data is variable (figure 21) and where it is unreliable (figure 22), useful data for further investigation of the dataset.

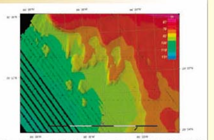

Figure 16: Shaded relief of one survey sheet. Projection: UTM Z16N on WGS-84. DTM generated by CUBE with no hand editing.

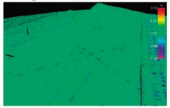

Figure 17: Difference surface color-coded over bathymetry, from south-east. Vertical exageration x32. Differences are mostly artifact.

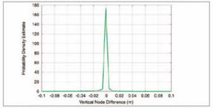

Figure 18: Probability density function estimate for figure 17. No significant statistical or hydrographic difference is observed.

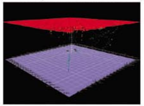

Figure 19: Extracted CUBE surface and raw data from which it was generated. Noisy data is mostly ignored, even given lack of density.

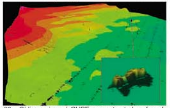

Figure 20: Oblique view of CUBE reconstructed surface from the north-west. Vertical exageration x32. Inset: a potential shipwreck.

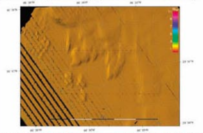

Figure 21: Shaded relief of unedited DTM, color-coded by number of hypotheses. Multiple hypotheses clearly show areas of difficulty.

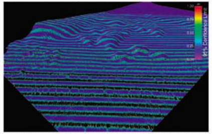

Figure 22: Low data density results in high uncertainty (color-coded over bathymetry). CUBE declines to use this data, causing holidays.