Model Based Processing for Simultaneous Mapping, Localization and Environmental Characterization in Underwater Environments

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1.0 ABSTRACT

US military undersea assets are being required to operate submerged for long periods in shallow water environments where use of the Global Positioning System (GPS) for navigation information is not available. New techniques need to be developed to fuse novel forms of sensor information with vehicle Inertial Navigation Systems (INS). This paper addresses the present US Navy investigation of using precision sonar sensing of the sea floor (bathymetry) and the acoustic environment to augment existing INS observations in order to enhance the performance of present systems. The fundamental algorithmic approach is to model the physics of all involved processes, and use Kalman or Particle Filters as predictor-correctors. Benefits will be demonstrated via analyses and simulations. We conclude by detailing simulation studies characterizing the performance improvement achieved from various model based algorithms for underwater military platforms.

2.0 UNDERWATER NAVIGATION REQUIREMENTS

According to a published article [1], the current US submarine force is beginning to utilize forward-looking sonar to navigate and chart the sea floor:

> [The Precision Underwater Mapping (PUMA) capability] "…relies on high precision, sonar-derived navigation, accurate profiling, and advanced CAD algorithms to generate high-resolution terrain and target maps of the seafloor in real time. While operating in poorly charted, extremely shallow waters, Asheville used this real-time data extensively for navigation safety."

The article also indicates these data are recorded so the observations can be used for correcting charts. As the main missions of the US submarine force are changing from blue water to shallower littoral combat areas, precise navigation in these areas while submerged (and thus out of GPS contact) has become a key area of technical research. Systems such as PUMA, which was originally designed for collision avoidance under ice operation, are being converted for use in bottom mapping and anti-mine warfare. Furthermore, the development and achievements of unmanned underwater vehicles (UUV) over the past decade have been remarkable. The rapid pace of technological advances in vehicle capabilities soon will result in UUV ranges approaching 2000 km and maximum depths exceeding 3000 m [2]. Again these systems require precise underwater navigation systems. However, some of the sensors needed to reap the benefits of these growing capabilities, such as forward-looking and navigation sonars, are not keeping pace.

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Requirements for underwater navigation are slightly different for submarines and UUVs. In the case of the submarine, the precision of the various systems depends on the class of vessel, and its associated sensor suite. The PUMA system is the first forward looking sonar (FLS) deployed for mapping and mine hunting.

2.1 Precision Underwater Mapping (PUMA) Navigation Issues

FLS systems such as PUMA can generate a single-ping bottom profiling in which an image of the bottom in front of the boat is generated based on the return of a single sonar ping (see Figure 1 for an example of such an image [1]). For this mode, the arrival angle and total round trip time of the sonar pulse is estimated for each range/bearing cell. This is then used to compute a bottom depth for each cell and the result is used to produce single-ping bathymetry display. This process of inverting the arrival angle and travel time uses the current best estimate of the SSP.

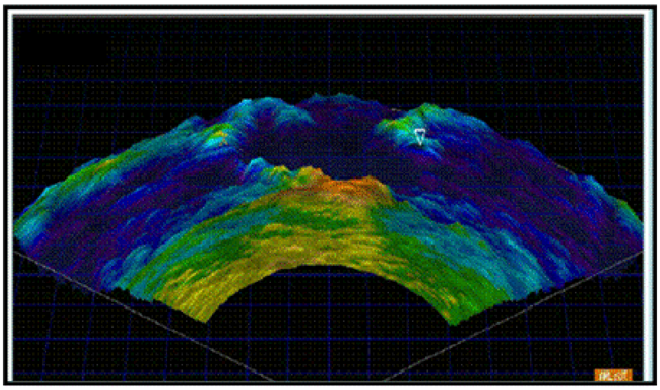


Figure 1: PUMA single ping bottom map (color represents depth)

Software can fuse several of these images to generate multi-ping charts (see Figure 2 for an example of such a chart overlaid with the boat track and the positions of several mine-like bottom contacts [1]). In this mode, several single-ping bathymetry maps (generated by the first mode above) are merged to produce multi-ping charts. The charts are generated using archived sonar data, and are usually reprocessed and corrected ashore using best estimates for sonar refraction effects from the environment's sound speed profile (SSP) and corrections for the boat Inertial Navigation System (INS) position.

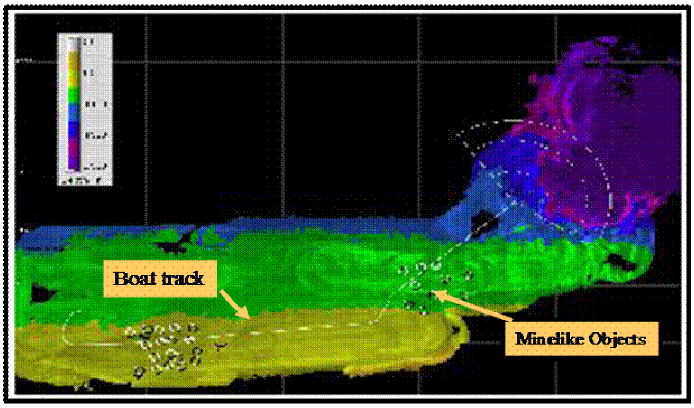


Figure 2: PUMA Multi-ping bottom map showing boat track and detected bottom contacts or "mine-like objects"

Limitations on the precision of the output of these systems exist because the current systems do not compensate for long term drift in INS, or variations in SSP from historic or *in situ* observations over time and distance. Both are sources of errors for mapping bathymetry and bottom object locations (i.e. mines and hazards). As a result, bottom maps currently generated on submarines are fairly precise, but absolute accuracy is uncertain in real time and corrections are only available at a later date.

Currently there are no mission requirements for forward-looking sonar (FLS) to be able to generate high quality bathymetric maps that can meet the IHO standard for hydrographic surveys sufficient to ensure safe passage (Order 2)[1]. Thus the current system does not compensate for the main sources of error for mapping bathymetry and bottom object locations such as mines and hazards. The two main sources for the errors are local variations in SSP from historic or even recent *in situ* observations, and long term drift in INS observations that accrue during prolonged submerged operation. These sources of errors cause errors in depth that are large enough to exceed Naval Bathymetric Standards, and errors in range which significantly reduce the value of mine-avoidance maps.

2.2 UUV Underwater Navigation Issues

There are several active US Navy UUV programs. UUVs have additional underwater navigation issues. Precision underwater navigation is required for the UUV missions of Surveillance and Reconnaissance, Mine Counter Measure, and Oceanographic Survey. The sonar and INS systems on board UUVs are smaller and more power constrained than those on submarines. This translates into either noisier sonar and INS measurements, or using costlier systems. The larger UUVs (such as the US Navy LMRS and MMRV) have a PUMA-type sonar (L-PUMA) which, though smaller and lower power, operates on the same principles as the larger PUMA system. Thus it has similar issues of precision and accuracy as found on submarines. Multi-beam and side-scan sonars (which look down and sideways respectively) are more common than FLS on smaller UUV platforms, resulting in a limited "look ahead" capability. Some UUVs carry a bottom-lock doppler sonar that can provide precise velocity information for precision underwater navigation, but which only works at limited height above the bottom. Finally, the issue of *in situ* SSP correction is even more critical for the UUV platform, because it operates in even shallower water than submarines.

2.3 Environmental Adaptation Issues

The sound speed along a sonar propagation path is often referred to as the mean sound propagation speed or, in the case of fathometers, simply the sounding speed. The precision and accuracy of navigation and bathymetric measurements obtained by sonar are directly affected by the uncertainty of sound speed along the propagation path. Thus, the mean sound propagation speed, not just the sound speed at the measurement platform, is needed by charting agencies to correct soundings and update charts. It is relatively easy and straightforward to obtain estimates of sound speed at the boat, as the instrumentation necessary for the measurement is standard on all submarines. It is also possible, though time consuming and costly, to obtain a depth-limited SSP directly below or above the boat[2]. However, it is not currently possible to estimate the mean sound speed along a radial propagation path, particularly over distances of several km in littoral waters where temperature and salinity are highly variable and vehicles must remain within their operating and mission envelopes.

Traditional sonar-based underwater bathymetry relies upon accurate measurement of the SSP in the area being surveyed, as errors in SSP translate to erroneous bathymetry measurements. In shallow water, where the SSP varies rapidly over both time and space, the measurement problem is even more complicated, as the profile may change drastically over the course of even a kilometre in travel due to salinity and thermal

[1] *The IHO standard for depth error is ~2.3% of depth for depths up to 200m. Position error is 20 m plus 5% of depth.*
[2] *Submarine expendable bathy-thermograph – used to measure the sound speed profile at the submarine. Deployment of an SXBT requires a special slow circling manoeuvre and cannot be done while the submarine is cruising.*

gradients. Furthermore, tidal effects and currents can drastically change the SSP over the course of a few hours. Thus, any sonar-based bathymetry technique must be able to measure the SSP *in situ* and in real-time in order to be applicable to coastal waters. This is especially true if the survey vehicle will inter-operate between both fresh and salt water areas. Such a capability for providing real-time bathymetry would greatly improve the operation of bottom mapping and anti-grounding sonar systems.

In deeper water, SSP mismatch also can lead to large errors due to the achievability of longer ranges. While the sound speed at a given depth may be measured quite accurately, currently one must directly measure the profile in the water column in order to accurately model the SSP. Furthermore, since ranges are longer, SSP variation due to fronts cannot be accounted for locally.

Thus to achieve precision navigation goals, future sonar and INS operation need to 1) automate calibration and SSP corrections, 2) improve forward-look bathymetry estimates by fusing returns from multiple pings, 3) automatically fuse sonar data with navigational information in an effort to reduce errors resulting from SSP mismatch, and 4) provide sonar observations of fixed bathymetric features back to the INS for correction of instrumentation drift.

3.0 MODEL BASED PROCESSING AND THE ADAPTIVE BATHYMETRIC ESTIMATOR (ABE)

The Adaptive Bathymetric Estimator (ABE) algorithm was developed to produce a high precision forward-looking bathymetric map while simultaneously estimating and correcting for changes in sound speed along the ray path, eliminating the need for *in situ* sound speed measurement. The technique is a Model Based Processing (MBP) application of the Extended Kalman Filter (EKF), which is used to fuse on-board navigational data of the vessel, multiple active forward-looking sonar returns from bottom contacts (time of arrival and arrival angle estimates), and underwater sound propagation parameter estimates from an internal ray-tracing model. The EKF effectively acts as a predictor-corrector, which iteratively estimates parameters for underwater acoustic sound speed and ocean bottom sonar contact positions based upon an internal underwater acoustic propagation model, and then corrects the estimates based upon the latest measurements from the platform's navigation and sonar system. Real-time quantitative measurements of consistency (convergence quality) and accuracy (estimation error) for the resulting bathymetry and sound speed estimates are generated as a by-product of the EKF algorithm.

The ABE technique extends the model-based underwater acoustics work of Candy and Sullivan [3] which has involved application of the EKF to several problems in the passive underwater sonar acoustics domain. These applications have included estimating sound speed profiles, environmental inversion using a normal mode model, passive source localization, and dynamic estimation of variable shallow water propagation model parameters. It has been the direction of ABE research to extend this model based methodology into the active sonar domain [4][5].

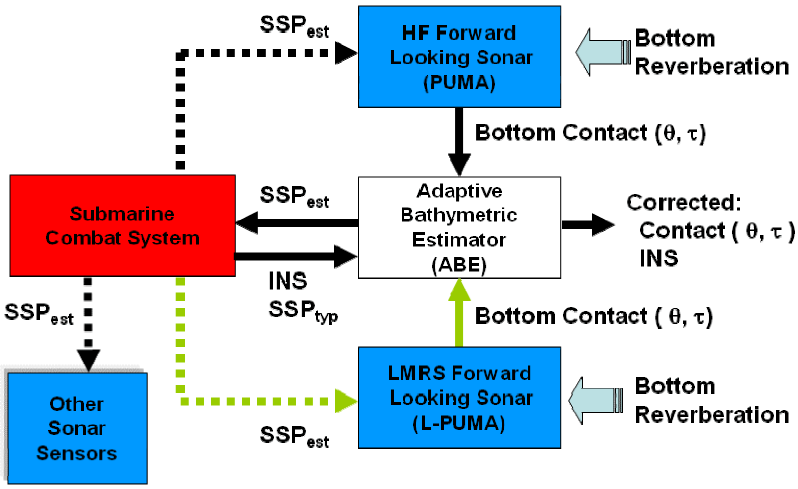


Figure 3: How ABE fits into the overall ASW combat system

The ABE can be thought of as a corrective lens for PUMA. Figure 3 shows a schematic of how ABE would interact with the rest of a submarine combat system. Primarily it would take as input from the combat system: current INS position, historical SSP information, and current sound speed readings, all of which are readily available in existing messages. It takes as input bottom contact information from the PUMA forward looking sonar system (shown here as time of arrival τ and angle of arrival θ though actual implementation details may vary). ABE then provides corrected INS, contact locations and SSP estimates to an operator or the combat system for use with other systems throughout the submarine. ABE could also process the outputs of a second forward looking sonar system, the L-PUMA carried by the Long-term Mine Reconnaissance System UUV. This deployable system operates in a similar manner as the PUMA. This application is the subject of current research. We expect that L–PUMA will benefit from ABE augmentation, especially since the mission profile of LMRS requires operation in very shallow water areas where SSPs are most variable, and underwater navigation precision is a premium requirement.

3.1 ABE and the Extended Kalman Filter

Figure 4 shows the structure of the EKF used by ABE. While the majority of the filter is standard, the design of the Internal State and Observation models are the major portions of the model development efforts. We will now describe the two models in a general manner.

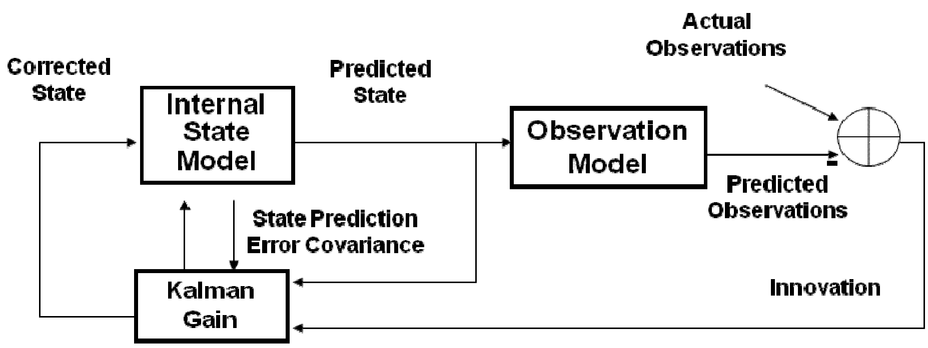


Figure 4: Block diagram of the Extended Kalman Filter

The Internal State model contains all the kinematic information of the submarine platform (position, velocity, acceleration, deterministic errors such as bias and drift), as well as the estimated position of a bottom contact (range depth), sound speed profile parameters (for example EOF coefficients to be discussed below), and random modelling errors such as errors in position due to currents.

The Observation Model contains the INS dead reckoning measurements, (own ship position, velocity, accelerations, roll, pitch, yaw), sound speed measurements (such as at the array), sonar measurements of bottom contacts (time of arrival τ, arrival angle θ) as well as the ray propagation model and observation errors (sonar ambiguity functions, beam steering error).

The EKF uses the Internal State Model to predict the state of the system during the next observation time, and generates predictions of what the corresponding observations should be. It then uses the difference between the prediction and the actual observations (the Innovation) to correct the state estimation. Portions of the innovation are generated by the mismatch in the sound refraction effects of the estimated SSP and the known SSP when imaging the bottom point. Further portions of the innovation arise from differences in the actual position of the sub, and the position obtained from the INS dead reckoning.

To summarize, ABE uses the EKF approach to achieve the following:

- Improve forward-looking bathymetric estimates (range and depth) over multiple pings. This is done much in the same manner that an EKF-based tracker improves the position and velocity estimates of a sonar contact – that is by using a kinematic model of the own ship motion, and the presumed static position of bottom contacts.
- Fuse dissimilar data sources such as active sonar returns (time and arrival angle measurements), navigation "ground truth" information (kinematics) and acoustic propagation model parameters. This fusion is one of the reasons why EKF has been so successfully applied to inertial navigation systems. We model the position and velocity of the submarine as would be supplied by the INS of the submarine. We will also model drift errors in position that arise from the dead reckoning used by the submarine.
- Estimate SSP characteristics. Embedded in the Observation Model of the ABE EKF is an actual model of high frequency underwater acoustic propagation (a ray-tracer), as well as a parametric model of the SSP. The parameters of the profile are augmented states in the EKF internal state vector, and are estimated along with the kinematic model parameters. This can be done even if they are not directly observable but only inferred by the apparent motion of the contact caused by refraction.
- Correct sonar measurements with estimated sound speed characteristics and corrected INS position information. This is a direct result of the predictor-corrector nature of the EKF.

3.2 Modelling Errors in Navigation and Assumed Sound Speed

Figure 5a shows a schematic of the effects of position error on the simulation. The primary position error arises from the submarine INS estimate of absolute position. We model the actual position as π and the INS dead reckoned (DR) position as ρ. At the start of a run it is assumed the submarine has just taken a fix of its position, such that the drift error is 0, i.e. that $\pi = \rho$. During the course of the run, a slight bias in the velocity measurement (known as β) accumulates, and the DR position starts to differ noticeably from the true position. This error in assumed ship position can actually cause apparent motion in the track of bottom objects, which ABE can then use to correct the INS position estimate (perfectly if there is no error in the sound speed used to compute the position of the target from the sonar measurements of τ and θ).

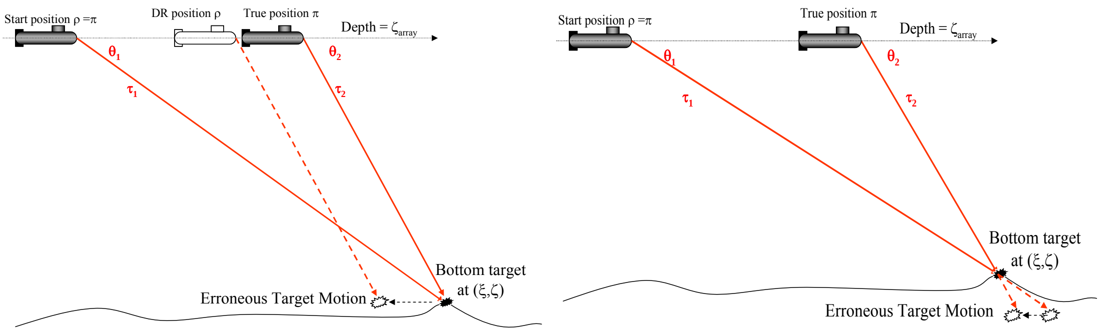


Figure 5a (left) 5b (right) : A schematic view of how errors in a) navigation due to drift and b) assumed sound speed can lead to apparent motion of sonar bottom contacts.

Sound travels between the sonar and the bottom contact along an "eigenray", which is straight in this illustration, but in general is curved. In the case shown in the figure, there is a fixed (negative) bias in the measured velocity such that the DR position of the ship is further to the left than it actually is. Ray tracing the position of the target gives an erroneous apparent motion on the bottom corresponding to a velocity equal to that of β. Estimating β in this case becomes a basic application of EKF for target tracking.

Similarly, if β=0, and the sound speed estimate used by the sonar system to compute target location was in error, then the scenario would look like that shown in Figure 5b. Here position is well known (at least on a systematic level – there are random measurement errors associated with the INS precision). The main error arises from using an assumed sound speed that is different than the true value. This type of error can also cause apparent motion in objects detected on the bottom, as well as provide erroneous depth information. In the case illustrated, the assumed sound speed is faster than the actual sound speed, so the sonar places the target farther along the sonar ray path (and deeper) than it actually is.

Drift error and sound speed miss-match both induce apparent motion in bottom target which ABE uses to correct estimates. Distinguishing between the two causes of motion is the tricky part. Fortunately, naturally occurring sound speed profiles produce curved eigenrays that disambiguate navigation errors from those due to sound speed mismatch.

3.3 Modelling the Shallow Water Environment

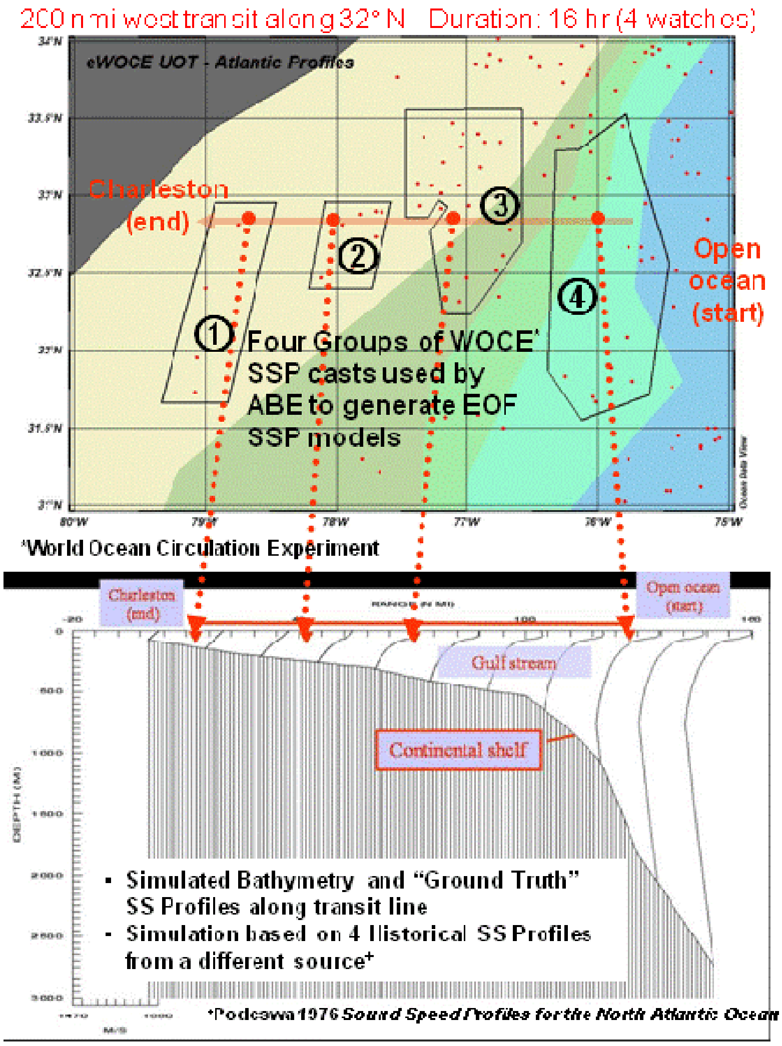


Figure 6: Typical shallow water environment used for simulations. Top shows transit of platform through the four geographic areas used to gather SSP casts into EOF groups. The bottom shows the bathymetry along the transit, as well as the variation in the archived SSPs from [6] and [7]

We have developed a shallow water environment scenario to illustrate the errors that can be caused by erroneous SSP assumptions. Because the deep [6] and shallow [7] water acoustic structure off the east coast of the U.S. is well documented and relatively complex, a 160 nautical miles (nmi) westerly transit along latitude 32.8 deg N during month of August was used as an illustrative example. This type of transit emulates the transit of a platform with FLS from deep water, where bathymetric estimates are not too critical, to shallow water areas of interest. This particular transit spans four distinct acoustic regions. Figure 6 illustrates the spatial dependence of sound speed and bottom depth for the baseline scenario along the transit. Figure 7 plots the SSP from 0 nmi along the transit along with the SSP from a point 120 nmi along the transit to show how different they are.

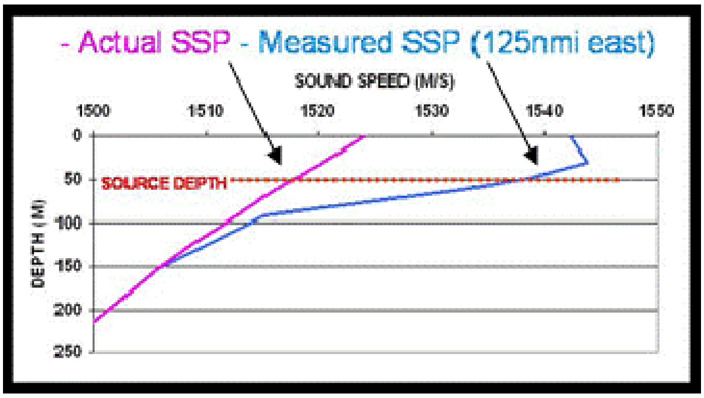


Figure 7: Sound Speed Profile (SSP) changes dramatically between the beginning (blue) and end (red) of the transit.

The ray trace for a case where the FLS is located at the range index of 120 nmi and depth of 60 m is shown in Figure 8a, with the appropriate SSP shown as the red line in Figure 7. The rays span the depression angles from 0 to –30 deg in one degree increments. This gives us a sonar signal that is resolved as an arrival angle which changes as a function of time. If the FLS is moved to a different location and the SSPs are not revised to reflect this change, the wrong sound speed profile will cause errors in the bathymetric estimates. The family of resultant ranges and depths represent the bathymetry estimate provided by a FLS using an outdated profile. Figure 8b illustrates the perceived bathymetry and ray paths based on an SSP at zero miles and arrival time and angles obtained at 125 nmi. For this notional forward looking sonar, we compute the estimated depth one mile in front of the sonar at 381 m but the actual depth is 210 m.

To model a more realistic and complex sound speed profile we need to use historical data that is less smoothed than that found in [6] and [7]. Our source for such historical sound speed profiles in the area of interest was the eWOCE Electronic Atlas of WOCE Data [8]. This is an open electronic data set that allows us to obtain historical instrumentation casts for the geographic area and calendar time of interest. SSP Locations in the eWOCE data base are shown in the upper part of Figure 6 by the red dots. These historical casts are used to develop the ABE SSP model described in a later section.

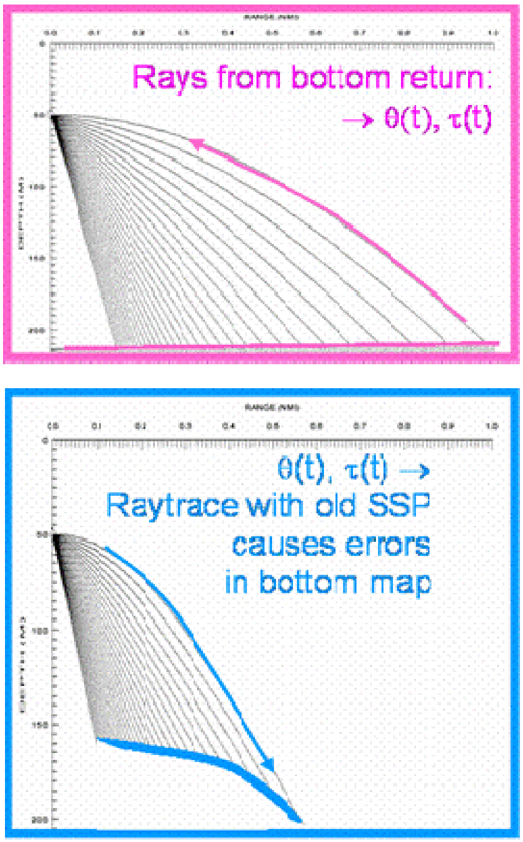


Figure 8a (top) and 8b (bottom): a) Eigenrays arriving at the sonar curve according to the red SSP in Fig. 7, resulting in sonar measurements τ(t), θ(t). b) Converting τ(t), θ(t) back to bottom coordinates by ray tracing with the outdated SSP causes significant errors in the bottom map.

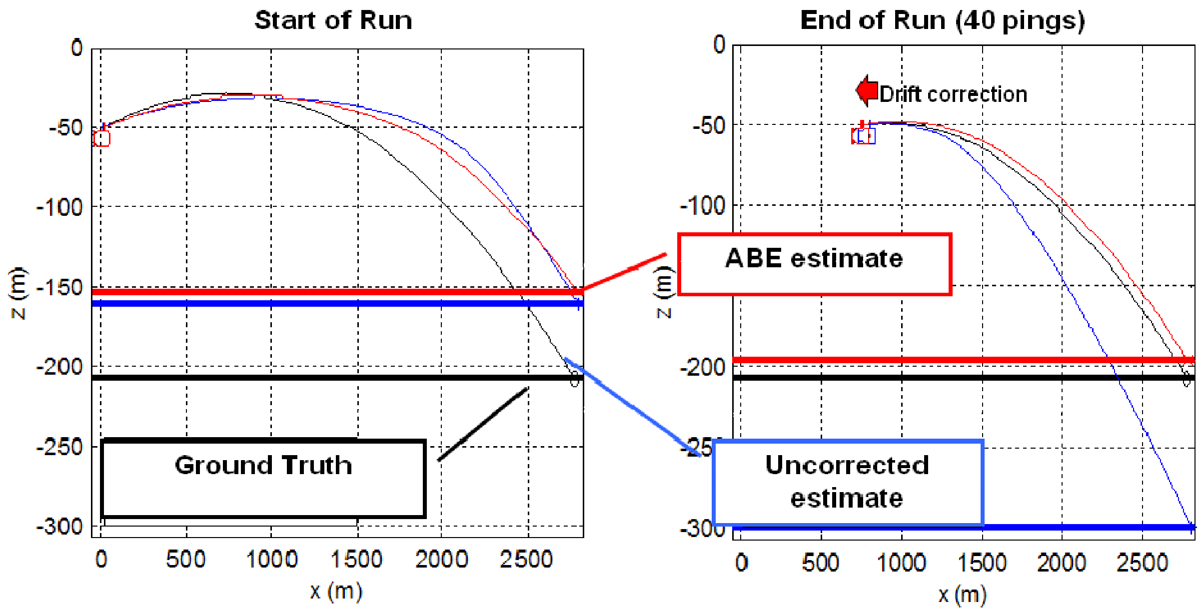
4.0 SIMULATIONS OF PERFORMANCE

4.1 Navigation Correction Example

As an example of ABE performance we use the simple SSP scenario of Figure 6. We constrain the boat and target to the x axis only. The boat position is at x=120 nmi, z = 50m, and the target position is at 121 nmi, with a depth of 207.6 m. The sound speed mismatch is as such: the boat assumed sound speed is that of x = 100 nmi (consider this to have been from an SXBT cast taken at the start of a watch, and that the sub has travelled 20 nmi and is now at the end of the same watch). The boat is assumed to have just taken a NAV fix, resetting β back to zero.

Figure 9a shows the results of ABE's eigenray, bottom position and platform position estimations after the first ping of the scenario. The ground truth eigenray is black, the eigenray derived from a ray trace using the old SSP information is blue, and ABE's first estimate of the eigenray is red. The eigenray is traced out to the uncorrected position of the bottom contact, but uses the estimated SSP. Figure 9b shows the same estimations after 40 ping cycles. The ABE estimated eigenray, bottom position and platform estimations all converge with the ground truth. While not shown, the estimate of the boat drift also converged to the correct value.

Our simulations show that the approach is sound. However, one cannot project these performance predictions into real-world operation. Analysis of ABE performance with sea-test data is part of our ongoing research.



Figures 9a (left) and 9b (right): A side view (depth is exaggerated) showing eigenrays from the sonar platform to a contact on the bottom. a) Start of the run after the first sonar ping. b) After 40 ping cycles, ABE's estimate of the bottom depth and compensation for the platform navigation drift approaches the ground truth.

4.2 Sound Speed Profile Estimation Example

Empirical Orthogonal Functions (EOFs) are the model that ABE uses to represent a complex layered sound speed profile. EOFs have been used by oceanographers for many years, as they present a way of representing a large family of measured profiles by the linear combination of a much smaller number of coefficients. The mathematics of the EOF is based upon the Singular Value Decomposition (SVD).

Figure 9 summarizes how EOFs are used by ABE. A set of historical SSPs are used as our input functions. A mean sound speed function is computed by taking the average sound speed at each depth point, and this mean is then subtracted from each of the profiles. The resulting functions of sound speed vs. depth are processed using the SVD, resulting in four Empirical Orthogonal functions, and four sets of four coefficients each, which can be used to recover each of the four original SSPs. The use of historical EOFs as a sound speed representation is well suited to the ABE formulation, as one only has to estimate one set of the coefficients.

We have begun to process recorded sea-test data with ABE in order to assess the performance of its SSP estimations. Our main difficulty as been in finding existing data sets with adequate ground truth information (since SSP casts are expensive to make).

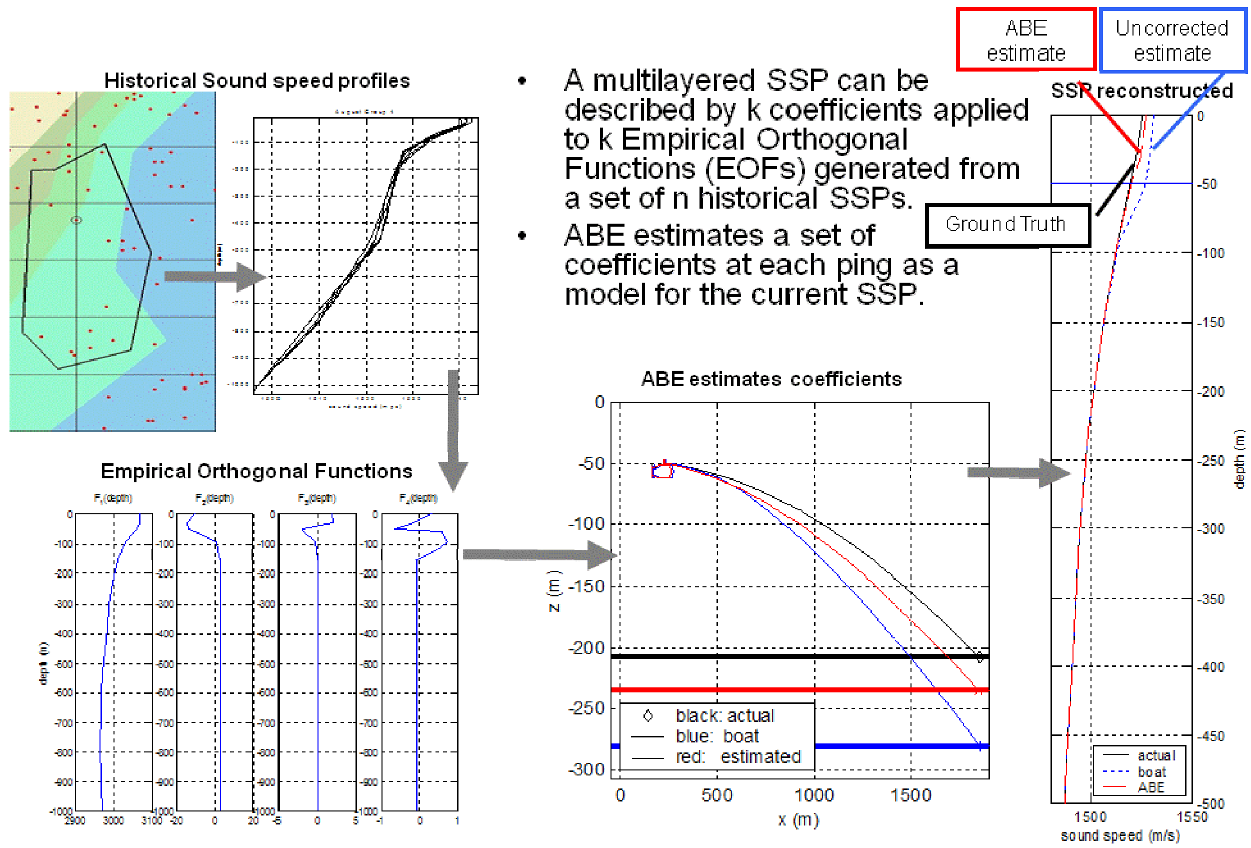


Figure 9: How ABE does sound speed profile modelling. Upper left: historical SSPs are selected based on hydrographical similarity (i.e. from areas with similar depth and acoustic properties). Four SSPs shown plotted on the same sound speed vs. depth axes. Bottom Left: Average SSP and three Empirical Orthogonal Functions resulting from a set of four historical sound speeds. Bottom Middle: ABE estimates the coefficients during a run. Right: The coefficients are used to reconstruct the best estimate of the SSP, which is then used by ABE's internal eigenray generators to correct the own-ship and contact positions.

5.0 MODELLING IMPROVEMENTS

The technology for Model Based Processing constantly improves. The continual reduction in computer hardware cost, and increase in computational power enable us to use more sophisticated models and estimation techniques. We will briefly describe two improvements that are currently the subject of our research.

5.1 Platform Modelling Improvements

While a constant velocity platform model is appropriate for a transiting submarine, it is not the best choice for modelling a platform that undergoes manoeuvres. Depth excursions can usually be accounted for by increasing the state noise for the platform depth variable, but turning platforms cause the EKF to generate large errors. This is exacerbated when modelling a UUV, as many littoral missions require UUVs to conduct search patterns.

The problem of designing an adaptive estimation algorithm that accounts for large changes in the kinematics of a manoeuvring platform can be approached in several ways. The approach we have chosen is to use a modification of the EKF known as multiple model algorithms. These assume that the system behaves according to one of a set of models (known as modes). The models can differ in both noise levels and structure. These models can be fixed or switching (according to a Markov chain), though we use the latter. A completely optimal solution is not computationally feasible, however a suboptimal approach called the Interacting Multiple Model (IMM) [9] has been providing robust results.

The IMM uses parallel EKFs each modelling a different manoeuvre. We use three EKFs operating concurrently: one for straight motion (as discussed previously), plus two more to model left and right turns with a constant turning rate. Additional models can be added with different turning rates as well. The IMM approach uses the EKF generated error statistics to compute the likelihood that each model fits the latest observation. The algorithm then merges the outputs of the models weighted by their likelihood into a final answer. This approach enables our tracking and localization algorithms to operate continuously during changes in platform heading. Furthermore, it is robust to modelling errors, because if one of the models starts to perform poorly (i.e. is mismatched to the actual process), its likelihood goes to zero and is eliminated from the output. If at a later point the model recovers and performs well, then its answer gets more weight and is included. Figure 10 shows a simplified case of two models and how their decision statistic is used to weight which model output to use.

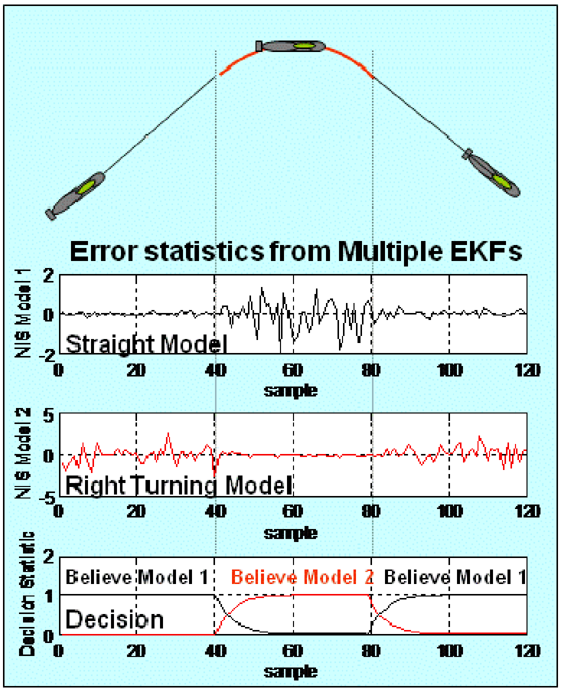


Figure 10: IMM approach mixes the output from multiple platform models, each with a different manoeuvre. The result is a more robust estimation of the platform position during manoeuvres

5.2 Model Estimation Algorithm Improvements

Oceanographic and bathymetric variability of littoral waters requires our estimation algorithms to be increasingly robust to nonlinear changes in the system. Also, environmental conditions may change more rapidly than an adaptive system response time. This is especially the case when rapid and dramatic changes in the acoustic propagation paths occur as the sonar platform changes depth. We have been investigating a new class of model-based estimation techniques known as Particle Filters [10], and the applications that have been developed by the robotics community for Simultaneous Localization and Mapping (SLAM) [11] [12]. The algorithm that we have chosen is the FAST Simultaneous Localization and Mapping (FastSLAM) [13]. MATLAB versions of this algorithm are available on the web [14]. This algorithm, which was originally designed for use with a robot vehicle (car) using LIDAR measurements to correct GPS and odometry, has been modified for an underwater vehicle and forward looking sonar.

The FastSLAM incorporates a new class of estimator known as the Particle Filter. Generally, these filters are superior to EKF in non-linear applications, providing faster convergence and increased robustness. This is achieved through the use of on-line Monte Carlo generation of probability distributions to minimize estimation error that arise from EKF linearization. In FastSLAM, the sonar platform location is represented as a "cloud of particles", whose distribution approximates the probability distribution of the state vector off the system. Each particle also has a likelihood associated with it. Each particle has multiple ABE-like EKFs to every bottom contact seen by the sonar, thus utilizing multiple simultaneous sonar contacts. Each particle has a complete time history of its path through the ocean. A best estimate of the path of the platform can then be generated from the weighted sum of the particle path (based on the particle likelihoods). The algorithm continuously and simultaneously updates the best estimated path of boat and position of contacts. When contacts are revisited, there is a built in probabilistic association based on distance from previously logged contacts that allows the system to combine data association of new tracks into the particle likelihood calculation. Thus this algorithm can correct for accumulated drift when the platform revisits previously logged contacts. This approach is well suited for platforms conducing search or mapping patterns.

We have begun simulation analysis of these algorithms. Figure 11a shows a top-down snapshot of a simulated run where the platform is utilizing multiple contact information. Figure 11b shows the platform in a later part of the run where it has turned and is revisiting several contacts. Most navigation errors are incurred during turns. The red track shows the platform making a major correction at the left most part of the turn when it sees the previously visited contacts for the second time.

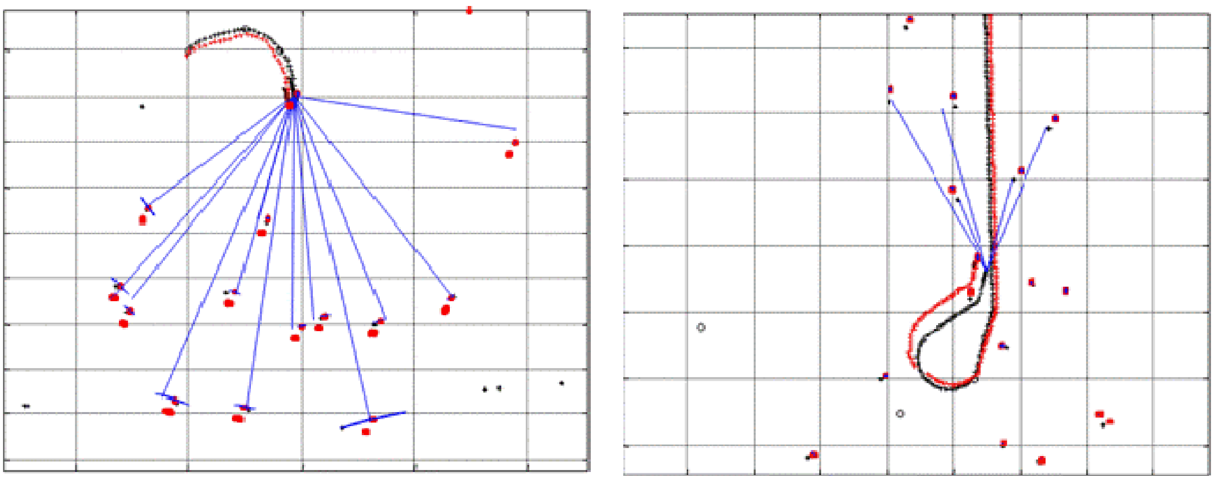


Figure 11a (left) and 11b (right): Top down geographic views of a FastSLAM Particle Filter simulation showing a) simultaneous use of 12 contacts and b) drift error correction when platform turns and revisits previously seen contacts. Dead reckoning track is black, corrected track and estimate of target positions are red, eigenrays to current contacts in blue.

6.0 CONCLUSION

We have shown that the fusion of sonar and INS sensor measurements can lead to improvements in both systems, and that this improvement can be used to enable precision underwater navigation. Our research is continuing in the use of Model Based Processing for precision underwater navigation. The majority of our work in the future will be the development of faster and more robust versions of the systems described in this paper. We would like to thank Dr. John Kim and ONR's Precision Navigation and Guidance Program for his continued support of this research, as well as Paul Koenigs and Michael Nicoletti from BBN for their contributions to this paper.

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