A POST-PROCESSING KALMAN SMOOTHER FOR UNDERWATER VEHICLE NAVIGATION

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Abstract - **This paper describes an automated post-processing tool, designed for use on navigational data gathered by autonomous underwater vehicles (AUVs), developed and operated by the Department of Ocean Engineering at Florida Atlantic University (FAU). The post-processing tool consists of a 9-state complementary error-state Kalman filter in conjunction with a Rauch-Tung-Striebel (RTS) optimal smoothing algorithm. The Kalman filter is run forward in time to merge navigational data from a gyroscope, a Doppler velocity log (DVL), a magnetic compass, a differential Global Positioning System (DGPS) receiver and an Ultrashort Baseline (USBL) tracking system. Subsequently, the RTS smoothing algorithm is run backwards in time to find and compensate for drift error in dead reckoned position and compass measurement error. The post-processing tool has been implemented as a graphical user interface, designed in MATLAB. Improved accuracy in position and heading has been verified by conducting sea trials and post-processing the collected data.**

I. Introduction

The Ocean Explorer (OEX) AUVs developed and operated by the Ocean Engineering Department at FAU are widely used as sensor platforms for various scientific missions. These sensors measure oceanographic parameters describing both the ocean and the seabed, as well as variables describing the position, speed, angular rates and orientation of the AUV itself. It is crucial for both of these types of data to be available within acceptable ranges of accuracy. Examples of AUV missions where this is obvious are seabed mapping, mine detection, pipeline route survey and water column classification.

For AUV technology development purposes, the data describing the vehicle dynamics are often of main interest, while the oceanographic data and other data describing phenomena external to the AUV are most important for commercial and/or military purposes. However, these data are usually not valuable unless they are accompanied by accurate data describing what the AUV was physically doing at the time. Therefore, for AUV applications in general, knowledge about the data describing the dynamics of the AUV is always important. This paper describes a post-processing method to greatly improve accuracy in AUV absolute position and heading data, *i.e.* to find out what the AUV *really* was doing throughout its mission. The data processing algorithm developed consists of a complementary Kalman filter [1] in conjunction with an optimal RTS smoother [2].

First, the subject of aided inertial navigation for AUVs is briefly discussed, followed by a description of navigation error sources for the OEX AUV. Next, the post-processing approach is given on a conceptual level, before being described in more detail in the next section. This is followed by a description of the Kalman Smoother GUI designed in MATLAB to operate the post-processing tool. Some analyses of results obtained are given, and results from sea trial experiments are shown.

Figure 1: Recovery of the OEX AUV

II. Aided Inertial Navigation for AUVs

The navigation system of an AUV usually consists of some sort of inertial measurement unit (IMU) in conjunction with aiding sensors such as a compass, DVL and a DGPS receiver. The IMU is an assembly of gyroscopes and accelerometers that measure the angular velocities and linear accelerations of the vehicle, respectively. Measurements from these instruments can be integrated with respect to time to obtain heading and position, given initial conditions. Inertial instruments are usually very accurate for short periods of time, but are subject to drift. Typically, the amount of drift is often inversely proportional to the price of the instruments. During a mission, the data from the IMU are merged with data from aiding sensors to adjust for drift in the inertially derived quantities. This is usually done by means of a Kalman filter. The data merging process is done in real time, and therefore the navigation solution will have unrealistic jumps due to unexpected position updates.

III. OEX Navigation Error Sources

During a mission, the OEX AUV typically starts by getting a good position reference at the surface, in form of DGPS fixes. The vehicle then dives to a preset depth to perform its task. While submerged the AUV estimates its own position by dead reckoning (DR), a process which consists of integrating up velocity measurements from a Doppler velocity log (DVL). Prior to the integration, the DVL velocities are rotated from body-fixed frame into North-East-Down (NED) geographical frame, by use the orientation angles from the compass (heading) and IMU (pitch and roll). Intermittently, the AUV will come to the surface for position reference, to be able to reset its navigation system. This is needed due to the drift that occurs in the DR position in the absence of accurate position reference. This drift is caused by measurement errors in the DR sensors (compass and DVL). The compass error causes cross-track drift, while the DVL error causes both along- and cross-track drift. In real-time navigation, the AUV has no way of sensing this drift as long as it is under water, where accurate DGPS fixes are unavailable.

The nature of the errors in the DR sensors are not always known a priori, and sensor calibration can therefore be inaccurate. The compass usually exhibits a heading-dependent error [3], resulting from both hard- and soft-magnetic fields generated by the AUV itself. This error may change between mission due to vehicle reconfiguration, and also during missions due to varying current-induced magnetic disturbances in the AUV. The DVL most likely has a scale-factor type error, that may result from sound speed inaccuracies and other acoustic phenomena [4].

IV. Conceptual Post-Processing Approach

The limitations seen in the accuracy of real time navigation solutions call for other approaches. One such approach is to post-process navigation data off line to produce a more accurate picture of the mission. In the post-processing scenario, the entire data set is available for analysis. The advantage to this is that all measurements can be utilized to estimate the state of the system at any point in time. This can be obtained by use of a forward-backward processing approach, where both past and future measurements are used in the estimation process.

By using the forward-backward processing approach, the final navigation solution will exhibit no unrealistic jumps. This is indeed due to the backward smoothing part of the estimation process, in which the growing drift errors are back-propagated in time and compensated for. A suitable technique to implement this approach is a complementary error-state Kalman filter in conjunction with an optimal smoothing algorithm that will filter the data forward and backwards in time, respectively [5]. The block diagram Figure 2 shows the approach on a conceptual level [4].

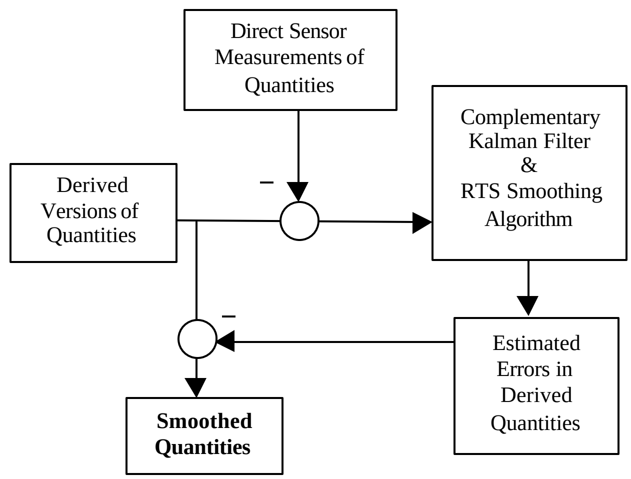

Figure 2: Conceptual Post-Processing Approach

The quantities referred to in Figure 2 are position and heading. Derived position is obtained by DR, using DVL and compass measurements, while derived heading is computed by integrating the yaw rate measurements from the gyroscope with respect to time. Since both position and heading are also measured directly by means of GPS/USBL and compass, respectively, two independent positions and headings are available for processing.

Furthermore, the two sets of position and heading have complementary error characteristics. While direct measurements contain both colored and white measurement noise (high frequency noise), quantities that are obtained through integration with respect to time, contain no white noise. However, these computed quantities will exhibit drift (low frequency noise), due to the colored part of the measurement noise in the variables from which they are derived. This intuitively suggests combining the two sets of data, thus exploiting the complementary characteristics of their respective errors. In essence, this is exactly what the complementary filtering approach taken in this paper attempts to do.

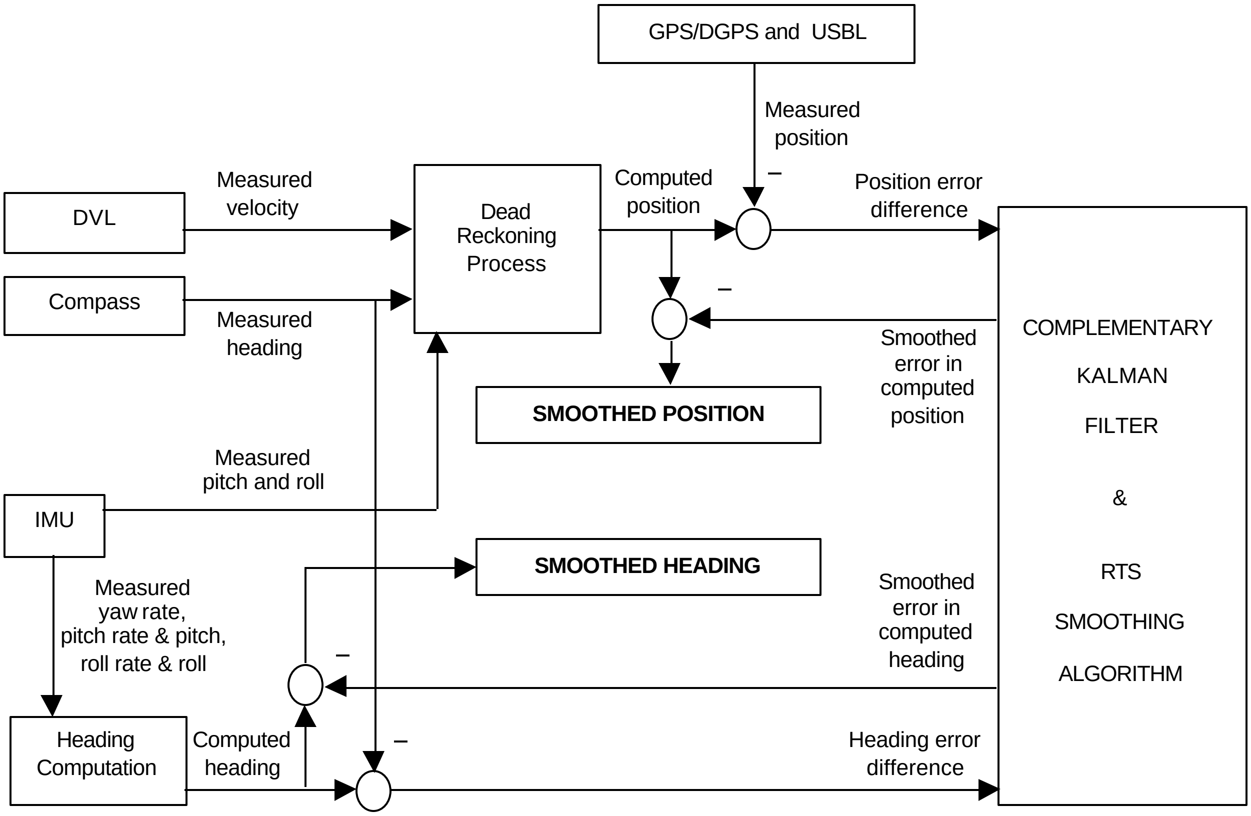

Figure 3: Navigation Data Flow

V. Kalman Smoother Design

The post-processing algorithm has been designed as an error-state complementary Kalman filter (CKF) with additional fixed-interval smoothing. The filter estimates drift errors in 2D position and heading, and also sensor errors in 2D position, heading, yaw rate and horizontal velocity. This generates a total of nine states, three of which represent drift errors and six of which represent sensor errors. Vehicle depth is not included, since it is assumed to be measured accurately enough by a pressure sensor.

Figure 3 shows the flow of data all the way from direct measurements to the final smoothed estimates of position and heading [4]. It is apparent that the CKF is actually updated with the difference between drift and sensor errors of the same quantity. This error difference is the result of subtracting the direct measurements of position and heading from their inertially derived counterparts. The following expression shows why this is true:

TRUE VALUE + DRIFT ERROR	(*computed*)
- (TRUE VALUE + MEASUREMENT ERROR)	(*measured*)
= DRIFT ERROR – MEASUREMENT ERROR	(*error difference*)

Furthermore, Figure 3 shows that the final estimates of position and heading are generated by subtracting the estimated drift errors from the corresponding derived versions of position and heading. This operation is visualized by:

TRUE VALUE + DRIFT ERROR	(*computed*)
- SMOOTHED DRIFT ERROR ESTIMATE	(*filter state*)
= SMOOTHED ESTIMATE OF TRUE VALUE	(*final estimate*)

The sensor errors have been modeled as first order Markov processes. Such process is given by the differential equation [6]

$$\dot{x} = \frac{1}{\tau}x + \sqrt{\frac{2\sigma^2}{\tau}}\,u(t)$$

where x is the error process, and $u(t)$ is white noise. This process is completely defined by its correlation time τ and variance σ^2. These parameters have been found empirically and through system identification methods.

The Kalman filter process matrix describes how the states of the filter are related to themselves. In this filter, the process matrix relates compass and DVL errors with drift error in computed position, and gyroscope error with drift error in computed heading [4]. Furthermore, the process matrix includes terms describing the models chosen for the different sensor errors. The process matrix is updated with the Kalman filter estimates, defining this as an extended Kalman filter (EKF) [7].

VI. Kalman Smoother GUI

A graphical user interface (GUI) has been designed in MATLAB for easy operation of the Kalman Smoother software [4]. The GUI provides for fast and automated post-processing and viewing of navigation data as soon as logfiles are available. In cases where logfiles are very large, and post-processing of the complete data set is inconvenient, partial extraction routines have been written in C to support the MATLAB code. The GUI includes options for tuning of all Kalman filter parameters and for setting mission-specific constants such as local latitude (for lat/long Earth coordinate transformations). Furthermore, the GUI has been designed so that processed workspaces can be saved and loaded for later viewing. The GUI main window is shown in Figure 4.

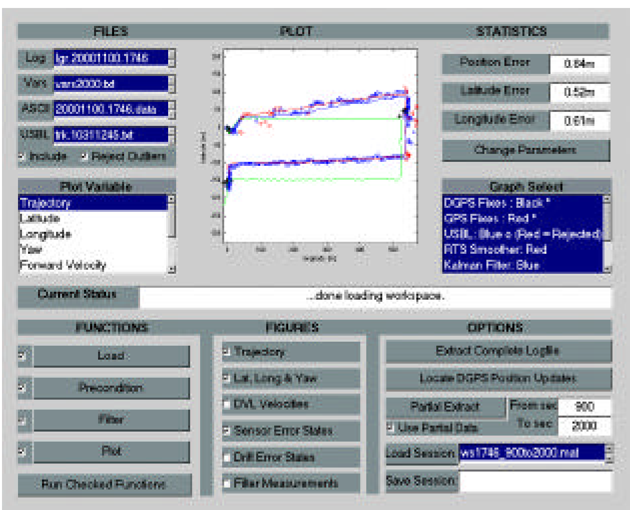

Figure 4: Kalman Smoother GUI

VII. Analyses of Post-Processing Results

Analyses of post-processing results have been done in order to evaluate the Kalman smoother's performance and capabilities [4]. Shown in this section is an underwater mission simulation done with data from a surface mission, and an analysis of how well the heading-dependent compass error is found by the Kalman smoother as a function of position reference availability.

The underwater mission simulation verifies improved accuracy in both position and heading, while the second analysis shows the main limitations of the post-processing tool.

A) Underwater Mission Simulation

Figure 5 shows the trajectory results after filtering and smoothing data from a heading setpoint mission in which the AUV was cruising straight West at 3 knots for about 500 seconds, and then straight East for the same duration. The vehicle was here cruising on the surface, with continuous DGPS coverage, and the strong southward deflection is due to ocean current. In order to simulate an underwater mission, most DGPS fixes were not given to the Kalman filter when post-processing. Fixes were given only at points where the AUV would typically come to the surface during an underwater mission. In this case fixes were given at mission start, in the middle of the first leg, in the turn, and at mission end. This approach produced artificial drift errors in the DR position as if the vehicle was cruising underwater. The effect is clearly seen in Figure 5, where the forward Kalman estimates follows the DR position, and resets itself whenever a DGPS fix is available. The improvement is obtained in the smoothed estimates, in which the DR drift error is observed and compensated for.

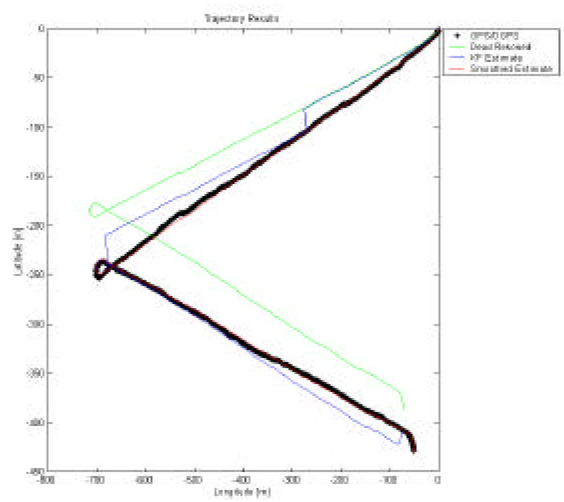

Figure 5: Underwater Mission Trajectory Simulation

Figure 5 shows that the smoothed position lies within 1-2 meters of the logged DGPS position; here assumed to be true. This corresponds to 0.2–0.4% of distance traveled between position references. Max position error seen is 5 meters, amounting to 1.1% of distance traveled between position references. The plot in Figure 5 has been scaled to accentuate the transverse drift of the AUV.

The heading accuracy achieved can be assessed by first quantifying the ocean current's contribution to the southward deflection. This contribution subtracted from the DGPS based course will be the AUV's true heading. Once the true heading is known, both the compass and Kalman smoother heading errors can easily be found. The following analysis is based on time averages.

The current-induced crab angles in the two trajectory legs is found by using the forward and starboard DVL velocities, and is given by:

$$\alpha^{T1} = \arctan\left(\frac{\mathbf{v}}{\mathbf{u}}\right) = -15.85°$$

$$\alpha^{T2} = \arctan\left(\frac{\mathbf{v}}{\mathbf{u}}\right) = +16.47°$$

where *T1* and *T2* denotes the two time intervals during the first and second leg, respectively, and **u** and **v** are the DVL velocities. The crab angles are referenced to the West direction in *T1*, and to the East direction in *T2*. The DGPS based course was found to be:

$$Course_{DGPS}^{T1} = 250.25°$$

$$Course_{DGPS}^{T2} = 105.63°$$

The true heading is therefore given by:

$$\psi_{true}^{T1} = Course_{DGPS}^{T1} - \alpha^{T1} = 250.25° - (-15.83°) = 266.08°$$

$$\psi_{true}^{T2} = Course_{DGPS}^{T2} - \alpha^{T2} = 105.63° - (+16.47°) = 89.16°$$

The compass reading during the two trajectory legs was:

$$\psi_{compass}^{T1} = 271.44°$$

$$\psi_{compass}^{T2} = 91.36°$$

This indicates a compass error given as:

$$\psi_{compass\,error}^{T1} = \psi_{compass}^{T1} - \psi_{true}^{T1} = 271.44° - 266.08° = 5.36°$$

$$\psi_{compass\,error}^{T2} = \psi_{compass}^{T2} - \psi_{true}^{T2} = 91.36° - 89.16° = 2.20°$$

On the other hand, the Kalman Smoother found the heading to be:

$$\psi_{smoother}^{T1} = 266.99°$$

$$\psi_{smoother}^{T2} = 89.58°$$

which indicates a smoother error of:

$$\psi_{smoother\ error}^{T1} = \psi_{smoother}^{T1} - \psi_{true}^{T1} = 266.99° - 266.08° = +0.91°$$

$$\psi_{smoother\ error}^{T2} = \psi_{smoother}^{T2} - \psi_{true}^{T2} = 89.58° - 89.16° = +0.42°$$

This amounts to a 82% reduction in compass error during both mission segments.

B) Ability to Detect Compass Error

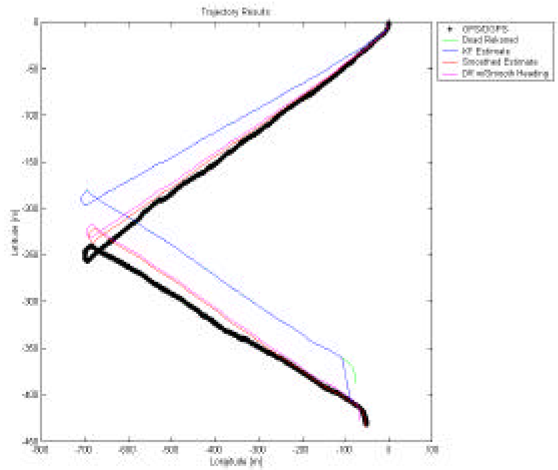

Figure 6: Poorly Detected Compass Error

Figure 6 shows the same mission trajectory, but here the Kalman filter has only been given DGPS fixes at mission start and end. It is seen that the smoothed position solution is degraded compared to what can be observed in Figure 5. This is due to the fact that the heading-dependent compass error has here not been found accurately, in fact the smoothed heading is as much as 2-3° off the true heading. This is a result of not providing the Kalman filter with accurate position reference close to where the compass error changes, *i.e.* in the turn halfway through the mission. This is the strongest limitation of the Kalman smoother, but is only an issue in cases where no USBL tracking data are available as additional position reference. A recalculation of the DR solution, based on post-processed heading data and raw velocity data from the DVL, is shown in magenta in Figure 6. The slight difference between this trajectory and the smoothed trajectory shown in red, suggests that the DVL also has a small error. The DVL error has not been found here, since velocity states were not used.

VIII. Sea Trial Experiments

A) Mission Description

The sea trial shown here consisted of an underwater lawnmower pattern, in which the short legs were incremented. This was done to investigate the behavior of the position error as a function of the length of the short legs, *i.e.* to see the effect of the distance between accurate position reference and the point at which the compass error changes. Furthermore, DGPS fixes were taken at every waypoint during the East/West legs, and at every other waypoint during the North/South legs. The AUV was tracked continuously by a USBL system mounted on the support vessel, and the tracker data was merged with the DGPS data in the post-processing to provide the Kalman filter with continuous position reference. Although noisy and biased, the USBL data is valuable information to the Kalman filter.

B) Results

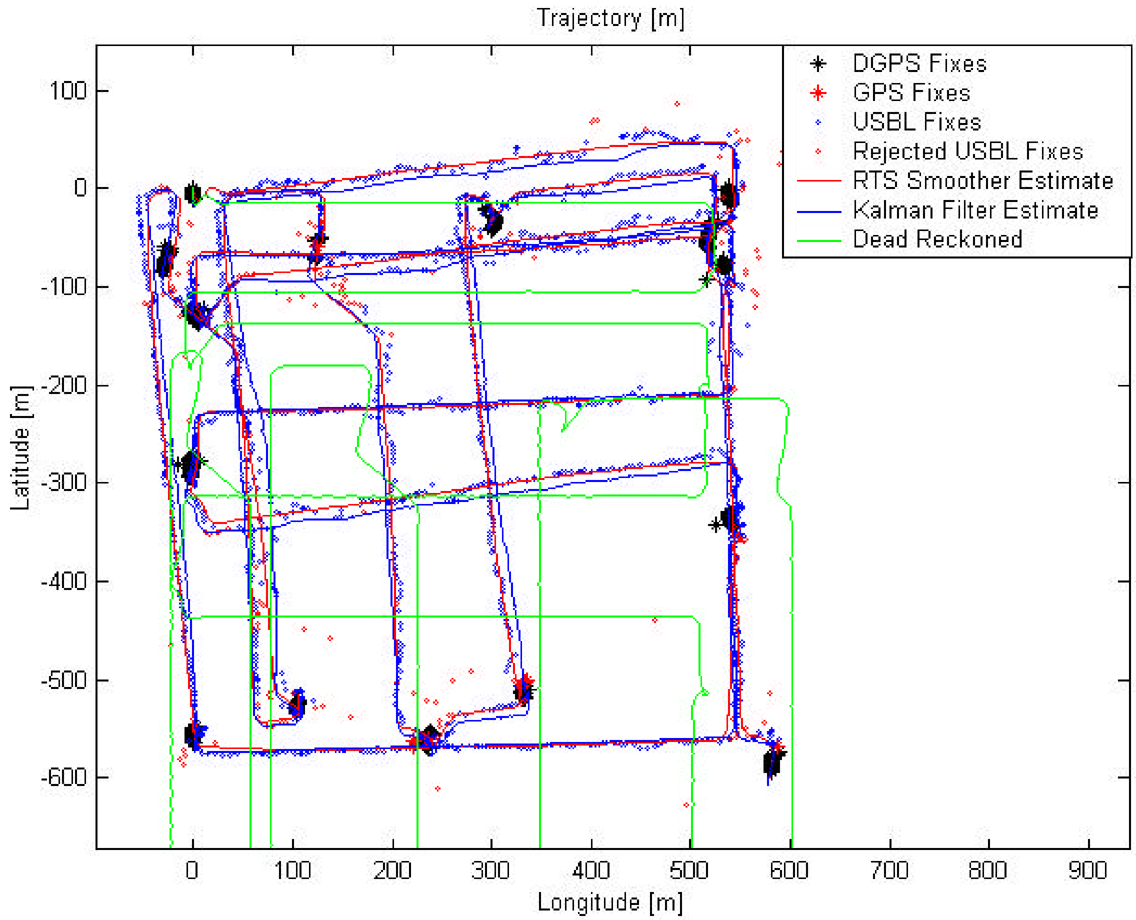

Figure 7: AUV Trajectory

The complete trajectory is shown in Figure 7, and the DR drift error is easily observed. It is seen that the smoothed position overlays the USBL tracking data, while maintaining the short-term smooth shape of the DR track. This is ultimately what is sought in a complementary smoother of this sort, *i.e.* that the long-term stability of the USBL data and the smoothness of the DR track are merged. Additionally, the DGPS fixes used are matched by the smoothed position to within 1 meter. The effect of an implemented USBL outlier rejection algorithm is also clear, which here seems to work well in cleaning up the USBL outliers.

Figure 8 shows some interesting features of both the forward Kalman filter and the backward smoother. In this particular mission it has been found correctly that the heading error is larger when going East (first leg) than when going West (second leg). The forward Kalman solution during the first leg is a compromise between the DR track going straight East and the USBL track's tendency of going North. This is because the compass error is so large (~ 6º), and in between USBL updates, the position solution relies on the DR track, thereby going straight East. This effect is less noticeable in the second leg because the compass error is smaller (~ 2º). The backward smoother, however, manages to do what the forward Kalman filter does not, namely to understand that there is in fact a permanent compass error while cruising East, and the resulting position solution passes right through the noisy USBL fixes.

The reason for the resemblance in shape between the smoothed position and the DR track is that the smoothed position estimate is ultimately based on the DR track and its accompanying drift error estimates, rather than on the USBL and DGPS measurements themselves [5].

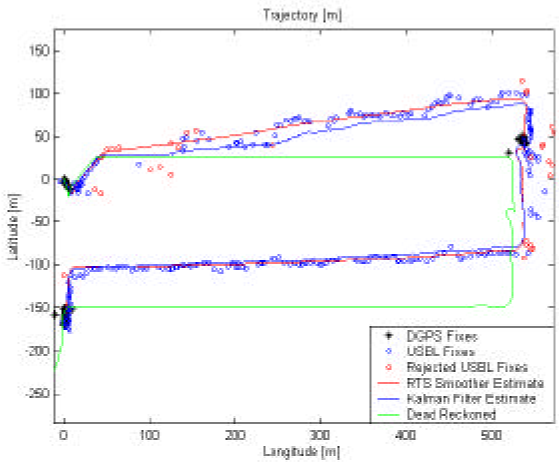

Figure 8: AUV Trajectory Segment

Figure 8 also shows the convenience of processing partially extracted logs, which is an option in the Kalman Smoother GUI. The trajectory segment shown can be processed in less than 3 minutes, while processing the complete data set takes on the order of 20-40 minutes, depending on system capabilities. This is particularly important if used in the field, when quick determination of AUV position at some point in time during a mission may be desirable. The analyst would then simply process the segment of the mission of interest, making sure that it encompasses at least two groups of DGPS fixes for proper position reference.

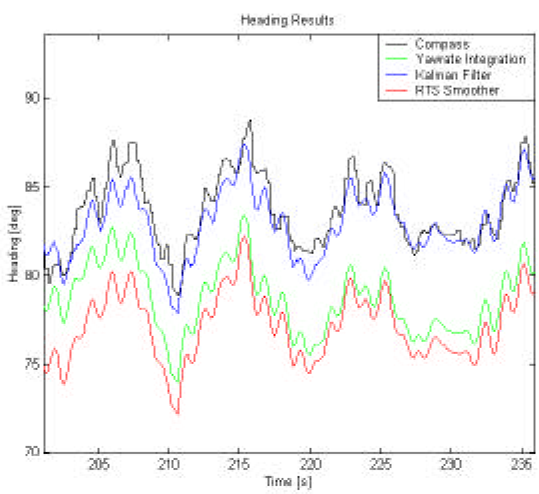

Figure 9: AUV Heading

Figure 9 shows a segment of the heading results from the sea trial experiment. Here, the Kalman filter has found the compass error to be around 5-7°. It is also seen how the shape of the smoothed heading resembles that of the integrated yaw rate, confirming that the complementary characteristics of the two available headings have been merged.

IX. Conclusions

The implementation of DGPS/USBL data merging is the main improvement to the present post-processing capabilities for the AUVs at FAU's Ocean Engineering Department. The Kalman smoother also provides means of post-processing mission data without the aid of USBL fixes, however this approach necessitates more frequent surfacings to get DGPS fixes. The Kalman Smoother GUI provides a convenient and efficient way of processing collected navigation data from an AUV.

The complementary filtering approach utilized has fulfilled its main goal, namely to merge the smoothness of integrated redundant versions of position and heading with the long-term stability of measurements of the same quantities. The Kalman smoother finds and compensates for DR drift and heading dependent compass error when provided position references close to where the compass error changes. The position updates can be in the form of GPS, DGPS or USBL. The result is greatly improved position and heading accuracy.

Crude error models for compass, DVL and gyroscope result in that the smoother needs frequent position measurements to provide good results. In particular, the smoother is not able to detect heading-dependent compass error without position reference close to where the change in compass error occurs. This is believed to be a result of the crude error models used. In these cases the position solution will also be of lesser quality due to the coupling between compass error and dead reckoned position. This limitation is only critical in cases where no positioning data are present.

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