Integrating DGPS-USBL position measurements with inertial navigation in the HUGIN 3000 AUV

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Abstract

Key words: AUV, DGPS-USBL, inertial navigation, Kalman filter, measurement delay

The navigation system of the HUGIN series of AUVs is presented. Both inertial sensors and aiding sensors are described. Particular attention is paid to the acoustic positioning system (DGPS-USBL). The Kalman filter equations used in HUGIN are shown. The problems caused by delayed measurements arriving out of sequence with other measurements are discussed. A solution to these problems is presented. The achieved accuracy of this system is documented.

Introduction

The HUGIN development program is a collaboration between Kongsberg Simrad and the Norwegian Defence Research Establishment (FFI). Three autonomous underwater vehicles have been produced so far. The objective of the HUGIN system is to collect data for detailed seabed mapping. The vehicles are fitted with a multibeam echosounder and other sonars for underwater surveys to depths up to 3000 m. HUGIN I had its first sea trial in summer 1996 and has been used as a test and demonstration platform. HUGIN II was put into commercial operation in the North Sea in 1998, offering services to the survey market. HUGIN 3000 was put into survey operation in the Gulf of Mexico in the autumn of 2000, see refs 1 and 2. The system is shown in Figure 1.

All the HUGIN vehicles have/will have an aided inertial navigation system. The navigation system provides data both to the Control & Guidance algorithms and to the mapmaking algorithms. High position and heading accuracy is needed both to ensure complete map coverage and to make accurate maps.

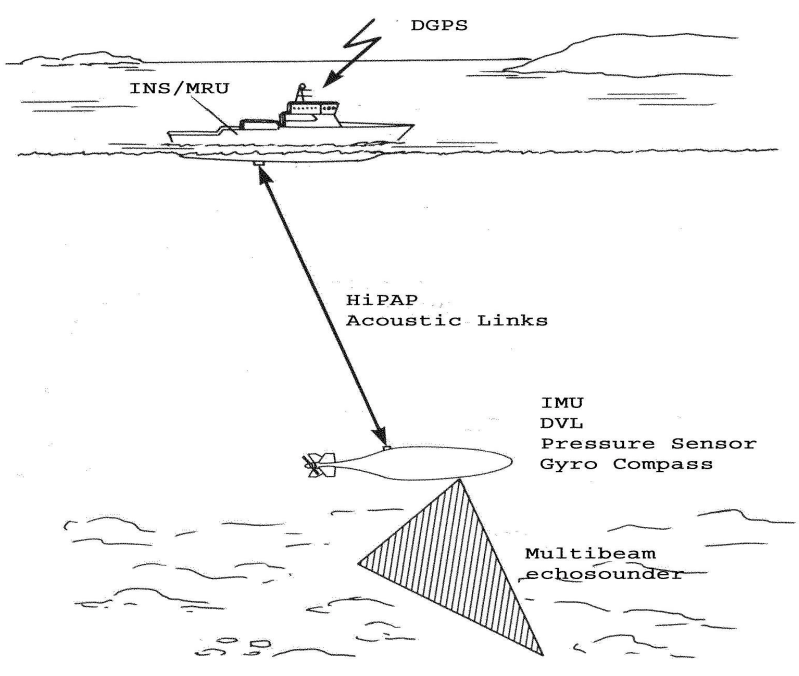

Figure 1: The HUGIN system

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The aided navigation system presented in this paper is currently used in HUGIN I and HUGIN 3000. HUGIN II is being fitted with the same system. The positioning accuracy has been verified and documented in surveys with HUGIN 3000 in the Gulf of Mexico. Earlier versions of the HUGIN system have been described in refs. 3, 4 and 5. These versions used compass and Doppler velocity log in a dead reckoning guidance system. There are several reasons for changing to an inertial system: It has made it possible to use waypoint guidance instead of course guidance, the system becomes less dependent on acoustic positioning, and the inertial system help correct the errors in the acoustic positioning system.

1. Navigation System Overview

The core of the HUGIN navigation system is a strapdown IMU (Inertial Measurement Unit). Currently the vehicles are fitted with the Honeywell HG1700 IMU, a 1 degree/h, 1 mg unit. The IMU measurements are used by the strapdown inertial navigation equations to compute position, velocity and attitude. These equations run at 100 Hz. The IMU parameters are given in Table 1.

	Bias	Random walk
Gyros	1 deg/h	0.125 deg/√h
Accels	1 mg	10e-5 m/s/√s

Table 1: IMU specification

As is well known, unaided inertial navigation will have an error that grows with time (low frequency error), so one needs aiding sensors to keep the errors down. The aiding sensors should have small low frequency error components so that they can check the long-term drift of the inertial navigation. In the HUGIN vehicles the aiding sensors are DGPS-HiPAP (Differential GPS – High Precision Acoustic Positioning), Doppler velocity log (DVL), Pressure sensor (depth) and Gyrocompass. In addition, roll and pitch measurements from an MRU (Motion Reference Unit) are used to initialise the inertial navigation. The DVL, Gyrocompass and MRU can also be used as a back-up dead reckoning navigation system.

Sensor	Bias (1σ)	White Noise (1σ)
DGPS	1.4 m	1.5 m 1D
HiPAP	0.0052*distance	Varying, 1 – 10 m
DVL	4e-3 m/s	6e-3 m/s
Gyrocompass	0.7°*sec(Lat)	0.01 deg
Pressure sensor	0.15 m	0.02 m

Table 2: Aiding sensor parameters

2. The Kalman filter

The best way of blending the measurements from the inertial navigation and the aiding sensors is with a Kalman filter. For background and theory on Kalman filtering, see ref. 6 or similar literature. The HUGIN vehicles use an extended error state filter. In this realisation of the Kalman filter the states are the errors in position, velocity, attitude (inertial states) and the biases in the sensors. The process model describes the integration of gyro and accelerometer errors to errors in position, velocity and attitude. It also models the autocorrelation of the aiding sensor errors. The differences between an aiding sensor measurement and the equivalent inertial navigation value are used as measurements for the filter. The navigation equations are reset with the error estimates each time a filter update is done. Using bar to indicate computed or predicted state, caret for estimate, tilde for measurement, the filter equations are:

$\underline{\bar{x}}$: Computed inertial data (attitude, velocity, and position).

$\underline{d\,x}$: Error in inertial data and biases in inertial and aiding sensors. This is the Kalman filter state vector.

$\underline{\tilde{y}}$: Measurement from aiding sensor.

Relationships:

$\underline{\bar{x}} = \underline{x} + N_x \underline{d\,x}$

$\underline{\tilde{y}} = \underline{y} + N_y \underline{d\,x} + \underline{w} = \breve{H}\,\underline{x} + N_y \underline{d\,x} + \underline{w}$

N_x, N_y : Picks the relevant elements from $\underline{d\,x}$

Kalman filter matrixes:

P : Covariance matrix of $\underline{d\,x}$

Q : Process noise matrix

R : Covariance matrix of $\underline{w}$

Φ : Transition matrix (time varying)

K : Kalman gain

H : Measurement matrix

Kalman filter measurement update:

$$\underline{z}_k = \hat{H}_k \underline{\overline{x}}_k - \underline{\tilde{y}}_k \quad (2.1)$$

Using the previous definitions, (2.1) becomes:

$$\underline{z}_k = H_k \underline{d\,x}_k + \underline{w}_k \quad (2.2)$$

$$K_k = \overline{P}_k H_k^T (H_k \overline{P}_k H_k^T + R)^{-1} \quad (2.3)$$

$$\underline{d\,\hat{x}}_k = \underline{d\,\overline{x}}_k + K_k (\underline{z}_k - H_k \underline{d\,\overline{x}}_k) \quad (2.4)$$

Resets:

$$\underline{\overline{x}}_k := \underline{\overline{x}}_k - N_x \underline{d\,\hat{x}}_k \quad (2.5)$$

$$\underline{d\,\hat{x}}_k := (I - N_x) \underline{d\,\hat{x}}_k \quad (2.6)$$

Kalman filter time update:

$$d\,\underline{\overline{x}}_{k+1} = \Phi_k \underline{d\,\hat{x}}_k \quad (2.7)$$

$$\overline{P}_{k+1} = \Phi_k \hat{P}_k \Phi_k^T + Q_k \quad (2.8)$$

Note that after a reset the estimate of the errors in the inertial data will be zero, while the estimate of the sensor biases is unaffected (partial reset).
A schematic of the navigation system is shown in Figure 2, the notation used is defined in ref. 7. In the following, the output from the block called Navigation Equations will be called inertial data. All sensors are synchronised to GPS time, and all sensor measurements are tagged (time stamped) with the time they were valid.

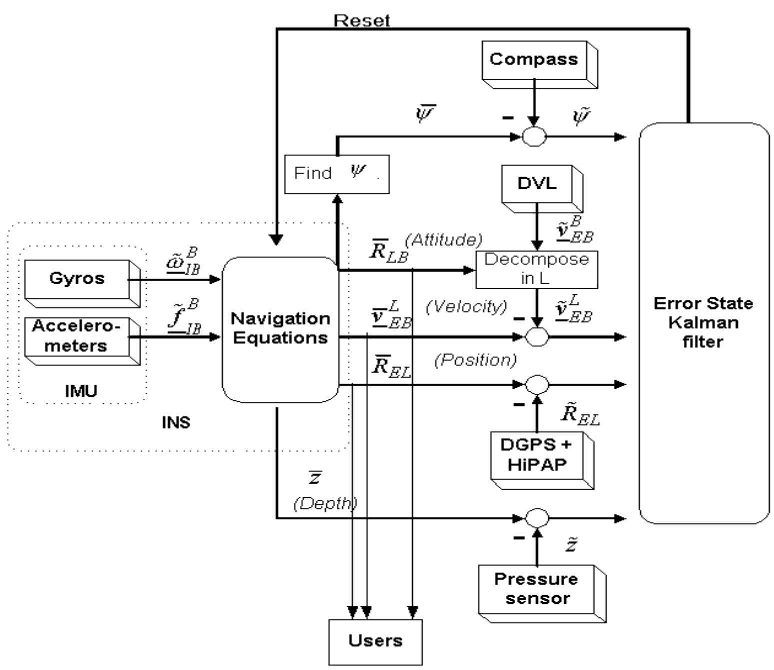

Figure 2: The navigation system

3. The DGPS-HiPAP system

HiPAP is an acoustic positioning system developed by Kongsbert Simrad. It is extensively used for dynamic positioning in the offshore oil industry. DGPS gives the position of the survey vessel's DGPS antenna while the HiPAP-system gives the HUGIN position relative to the HiPAP-transducer on the survey vessel. The HiPAP position is given in a transponder co-ordinate system, hence the vessel's attitude must be known in order to transform it to geographic co-ordinates. Since HiPAP and DGPS are installed in different locations on the ship, the distance between them must be taken into account when HUGIN's global position is calculated. This must be done when the system is installed on a new vessel.

Typically DGPS systems have an accuracy of 2 m (2σ) whereas RTK GPS is in the sub-meter region. For both systems the error is modelled as a combination of colored and white noise.

HiPAP is a USBL (Ultra Short BaseLine; also known as SSBL, Super Short BaseLine) acoustic positioning system that produces its position estimates based on measurements of horizontal bearing, vertical bearing and distance, ie pointing direction and distance. The measurements are done on the survey vessel, and the combined DGPS-HiPAP position is transferred to HUGIN via acoustic link. For moderate vertical angles, the bearing accuracy is 0.1° to 0.3° (1σ) (depending on signal to noise ratio) and the distance accuracy better than 0.2 m (1σ). The most important error sources are:

- The vessel's noise spectra (a sufficient signal to noise (S/N) ratio must be achieved)
- Raybending due to variation in density, temperature and salinity (the sound velocity profile must be compensated for)
- Errors in the vessel's roll, pitch and azimuth.

Clearly, the HiPAP position error increases with depth/distance. Calculated HiPAP circular position accuracy at different depths is shown in Table 3.

AUV depth	HiPAP circular position accuracy (1σ). (Bearing accuracy: 0.3°)
300 m	1.7 m
1000 m	5.3 m
1300 m	6.8 m
2000 m	10.5 m
3000 m	15.7 m

Table 3:Theoretical HiPAP position accuracy as a function of depth. The relative position between the AUV and the survey vessel is x = 100 m, y = 100 m.

Provided correct sound velocity profile estimate, there is no constant bias in the HiPAP position error. Constant position errors can not be estimated without a second source of globally referenced position measurements. The combined DGPS-HiPAP position error is modelled as a sum of coloured noise and white noise in the Kalman filter.

The HiPAP-system in HUGIN configuration will usually have a measurement rate of approximately 0.25 Hz. Due to the limited bandwidth of the acoustic links, position is only sent to HUGIN every thirty seconds.

Under certain circumstances the HiPAP-system can lose track of the AUV, for instance due to propeller noise when the AUV is close to the surface. It may then give false positions due to multipath effects. To avoid false measurements being sent to the AUV a wildpoint filter is implemented on the survey vessel. The filter is based on knowledge of the AUV dynamics and the DGPS-HiPAP noise. Since all topside measurements are stored on disk it is possible to do better filtering offline.

4. Measurement delays

Measurement delays (delay between the time a measurement is valid and the time it is available for the Kalman filter) will exist in all real time systems. When data is transferred on an electronic network, these delays will be small, typical delays for the onboard sensors in HUGIN are < 0.1 second. The DGPS-HiPAP position is different: It is transferred on an acoustic channel and the positioning itself takes time, both due to processing time and the physical constraints of sound velocity. This, in turn, means that the time delay from a position measurement is valid (and time stamped) until it is delivered to the HUGIN navigation system is significant (several seconds). These measurements will arrive out of sequence with the measurements from the onboard sensors. The problem with that is that each velocity measurement (1 Hz) also enables the Kalman filter to make an estimate of the position error. This means that by the time a position measurement for a given point in time is received, part of the position error at that time has already been observed through the velocity measurements and the inertial position has been reset accordingly. Figure 3 shows how measurements arrive. In general, there are three times of interest in the navigation system:

t_{rt} : Real time.

t_m : Measurement time (time stamp of measurement).

t_{kf} : Last time the Kalman filter was updated.

Without delays in the system $t_m = t_{rt}$ and the Kalman filter would be propagated from t_{kf} to t_{rt} before a measurement update was done. With delays $t_m < t_{rt}$ and we might also have $t_m < t_{kf}$. It should be stressed that all delays in the HUGIN system are known. Unknown delays create another order of problems than those discussed here.

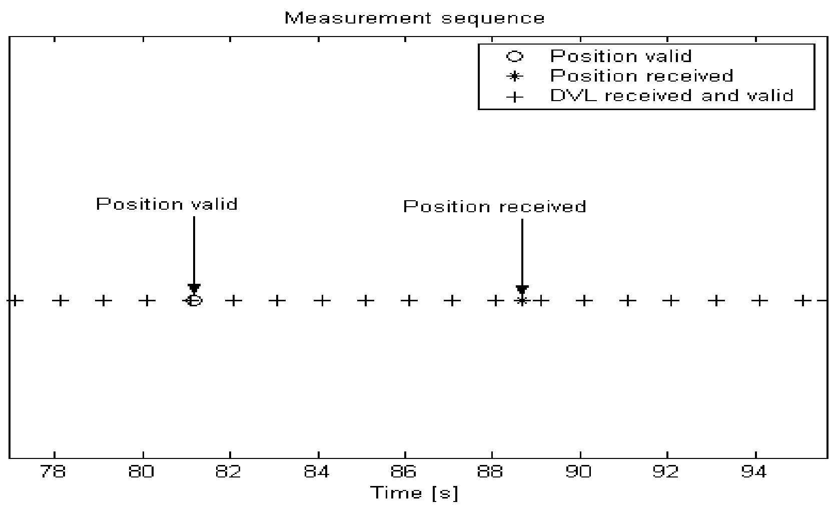

Figure 3: A typical measurement sequence

5. Possible solutions to the delay problem

There are several ways the problem of severely delayed measurements could be solved. This chapter will give a brief, general discussion of some of them. Solutions involving changing the policy of resetting the inertial data each time a Kalman filter update is made will not be discussed. These kinds of solutions were considered to be too costly in terms of SW development and verification.

Solution A: Run all as real time

This solution entails processing the aiding sensor measurements as they arrive and always using the latest inertial data to make the measurements for the Kalman filter. Measurements for the Kalman filter are made using the inertial data valid when the aiding sensor data is received. The solution is equivalent to changing the timestamp of the measurement to the present time, i.e. saying that $\underline{\tilde{y}}_{rt} \cong \underline{\tilde{y}}_m$, and make equation (2.1)

$$\underline{z}_{rt} = \hat{H}_{rt}\,\underline{\bar{x}}_{rt} - \underline{\tilde{y}}_m \tag{5.1}$$

For this assumption to be valid the difference due to the time delay must be much lower than the errors in the measurements. HUGIN has a speed of 2 m/s and the time delays can be up to 12 seconds, which would cause an error of 24 m for a delayed position measurement. This is clearly too large given the error characteristics of the DGPS-HiPAP system.

Solution B: Run navigation at fixed delay

The solution entails holding (storing) the aiding sensor and IMU data in queues until a time limit is passed. The time limit would be based on the maximum expected delay in the HiPAP-measurements. The sensor data would be sorted according to their timestamp and the navigation equations and the Kalman filter would process them in the correct sequence, but all data would be for instance 12 seconds old by the time they got to the users. While this would give optimal Kalman filter estimates, running the Control and Guidance algorithms on data that was 12 seconds behind real time would clearly be too much.

Solution C: Run inertial navigation in real time, Kalman filter at fixed delay

In this solution, IMU data is processed in real time, while measurements from aiding sensors are stored until a time limit is passed. The aiding sensors would be sorted according to their timestamp, and measurements for the Kalman filter would be made with the inertial data valid at the aiding sensor timestamp. The inertial navigation would be reset with errors valid up to 12 seconds ago. Under the assumptions that errors are not changing significantly during the delay (corresponds to $d\underline{x}_{rt} \cong d\underline{x}_m$) and that the error is not of a size to require immediate action, this would not be a problem. However, if HUGIN runs without HiPAP and DVL for some time, immediate action may be required. This solution has therefore been ignored.

Solution D: Run inertial navigation and Kalman filter in real time, redo navigation and filtering when old measurements arrive

All IMU and aiding sensor data are processed when they arrive, and also stored together with the Kalman filter covariance matrixes. When a delayed aiding sensor measurement arrives, the Kalman filter measurement is made with the inertial data valid at the aiding sensor timestamp. The inertial data for t_m are reset and all stored measurements (both IMU and aiding sensors) are processed again from the measurement time and onwards. This solution would always provide the users with the best possible data in real time. At the same time it would make the best possible use of the aiding sensors, without making any assumptions about the development of errors or the full states. However, it is too CPU-intensive to be used in HUGIN.

Solution E: Run inertial navigation and Kalman filter in real-time, make delayed measurements

In this solution, inertial navigation and the Kalman filter are run in real-time, but measurements are compared with the inertial data from the time the measurement is valid (t_m), and the Kalman filter uses the difference $\underline{z}_m$ in real-time. In more detail:

Measurements for the filter are made using inertial data with the correct time stamp, but processed with the current covariance matrixes and estimates in the Kalman filter. Resets are done on the current inertial data. This is similar to Solution A, but now assuming that the *error* is not changing significantly during the delay. The state update equations will be:

$$\underline{z}_m = \widehat{H}_m \underline{\overline{x}}_m - \underline{\tilde{y}}_m \tag{5.2}$$

$$\underline{d\hat{x}}_{rt} = \underline{d\overline{x}}_{kf} + K_{kf}(\underline{z}_m - H\underline{d\overline{x}}_{kf}) \tag{5.3}$$

$$\underline{\overline{x}}_{rt} = \underline{\overline{x}}_{rt} - N_x \underline{d\hat{x}}_{rt} \tag{5.4}$$

Note that K_{kf} is not the gain used at t_{kf} but a gain computed from P_{kf}. This solution gives the users good real time data, and the only assumption made is that the errors won't change much during the delay. This will be true in the HUGIN case, since the DVL and compass will limit the error growth in position. The solution is not CPU-intensive nor does it require memory to store old matrixes. For these reasons, this is the solution that has been implemented. However, implementing it is not quite straightforward when running the filter with resets.

6. The effect of resets

If the filter was running without resets, the a priori estimate $\underline{d\overline{x}}$ in equation (5.3) would give the current estimate of all errors, while their covariance would be used to compute the Kalman gain, K_{kf}. There would be a slight mismatch between the measurement and the covariance used to compute the gain, but under the assumption that the errors are changing slowly, this hardly matters. It is more important that the Kalman filter uses the already established covariance to make the most of the measurement.

When navigation is run with resets, the situation changes. While errors are slowly changing, the *estimates* of errors can change rapidly. If we introduce $\underline{dc}$ as the error without resets, we have

$$\underline{d\overline{x}}_{kf} = \underline{d\overline{c}}_{kf} - N_x \sum_{1}^{kf} d\,\underline{\hat{x}}_i \tag{6.1}$$

$$\underline{\overline{x}}_{rt} = \underline{x}_{rt} + d\,\underline{c}_{rt} - N_x \sum_{1}^{kf} d\,\underline{\hat{x}}_i \tag{6.2}$$

$$\underline{\overline{x}}_m = \underline{x}_m + d\,\underline{c}_m - N_x \sum_{1}^{m} d\,\underline{\hat{x}}_i \tag{6.3}$$

The underlying assumption $d\,\underline{c}_m \cong d\,\underline{c}_{kf}$ still holds, but it is quite clear that $\sum_{1}^{kf} d\,\underline{\overline{x}}_i <> \sum_{1}^{m} d\,\underline{\overline{x}}_i$ when $t_m < t_{kf}$.

A $\underline{z}_m$ taken directly from (5.2) will not match the error estimate that is incorporated in $\underline{\overline{x}}_{rt}$. The estimates from t_m to t_{kf} are not visible in $\underline{d\overline{x}}$, since the state vector has been reset. At the same time, the latest estimates are not visible in $\overline{x}_m$, since the resets were done later. This means that the full state in real time contains information that is no longer visible to the Kalman filter. Thus, if nothing is done, an error known and corrected at t_{kf} can be estimated as a new error from z_m. The navigation equations could end up being reset twice or more for the same error, which could lead to oscillations in the filter. To get around this problem, the HUGIN navigation system stores all estimates when they are computed. The stored values are used to correct the equations, so that Equation (5.2) becomes

$$\underline{z}_m = \widehat{H}_m(\underline{\overline{x}}_m - N_x \sum_{i=m}^{kf} \underline{d\hat{x}_i}) - \underline{\tilde{y}}_m \tag{6.4}$$

This in turn is processed through equation (5.3) and (5.4) in the Kalman filter.

7. Navigation system accuracy

In detailed seabed mapping, it is the position accuracy of the produced maps, the digital terrain models (DTM), which is of primary interest to the user. A complete DTM position error budget has been presented in ref. 8. The DTM position accuracy is a function of AUV navigation system accuracy, survey vessel attitude accuracy, survey vessel systems installation accuracy, multibeam echosounder position accuracy, AUV systems installation accuracy and AUV clock drift. In Figure 4 the predicted AUV navigation system accuracy and DTM position accuracy for varying depths are shown. Comparing the navigation system accuracy graph with Table 3, we see that the inertial navigation system accuracy improves the DGPS-HiPAP accuracy considerably. AUV INS heading accuracy is in the order of 0.2°.

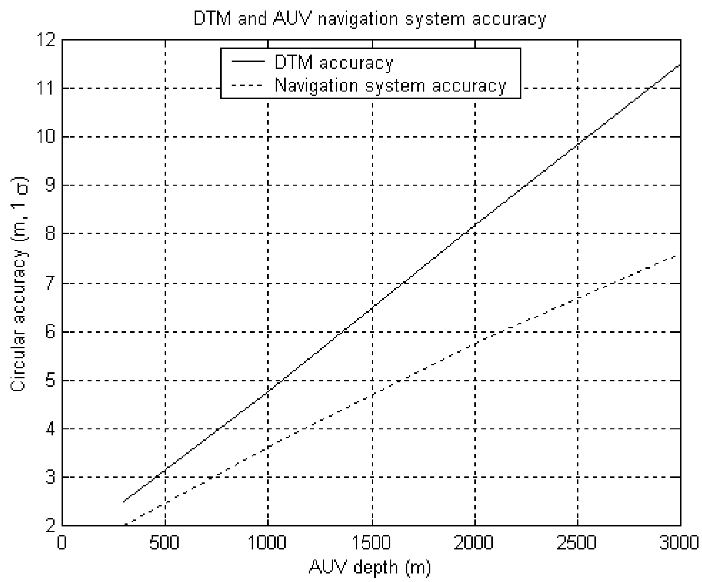

Figure 4: AUV navigation system position accuracy (dotted line) and resulting DTM position accuracy (solid line) for varying water depths.

We are now in the process of verifying the navigation system accuracy in sea trials in varying water depths in the Gulf of Mexico. The method used is mapping a known object, typically a well head, multiple times with reciprocal lines in different directions. Figure 5 shows the ”wagon wheel” pattern when mapping a well head in 1300 m water depth. The well head, hardly visible in this coarse figure, is in the middle of the intersected lines.

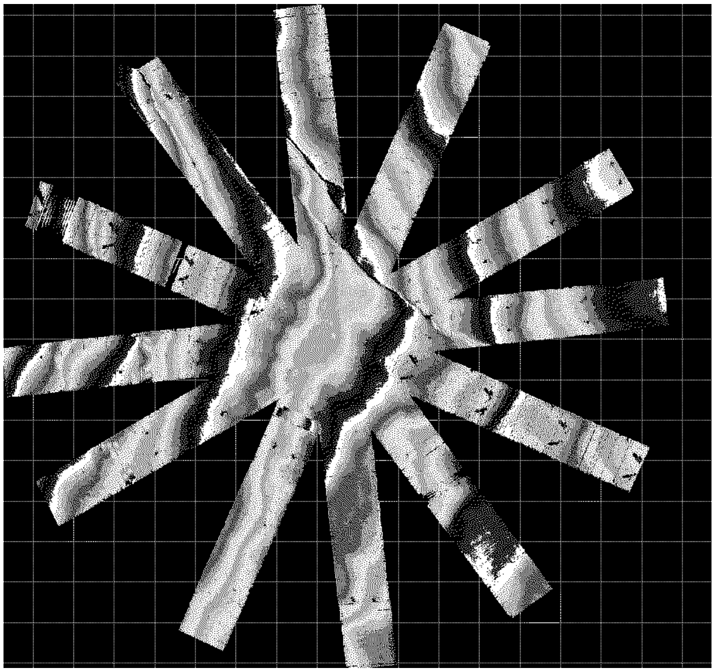

Figure 5: Lines with multibeam echosounder data collected for navigation system accuracy verification in 1300 m water depth. A well head with known position in the middle of the intersected lines is mapped multiple times.

In Table 4, results from two accuracy tests in 1300 m are shown. "Ref difference" is the difference between the mean value of the DTM observation and the pre-surveyed position of the well head. The well head was deployed from the BP drill platform Ocean America in 1999 and was positioned by determining the surface position of the drill string using DGPS. The drill string had a heavy well guide attached to the end. This made the drill string almost vertical but uncertainty of the effect of water current on the drill string is the largest source for position uncertainty.

The position accuracy can be improved by post-processing the data with a forward/backward smoother, compare the "KF Std dev" in Table 4. The smoother produces an optimal estimate based on all logged measurements from both history and future. Furthermore, the full set of position measurements stored on the survey vessel is utilized.

The Kalman filter standard deviations are well in accordance with the standard deviation of the well head observations (population standard deviation), though the March 2001 post-processed results are a little high. Given the uncertainty of the verticality of the drill string, the "Ref difference" results are consistent.

Depth	Mission	No. of meas.	Ref difference		Pop. Std dev		KF Std dev	
			North	East	North	East	North	East
1300 m	March 2001 real-time	6	1.2 m	6.1 m	2.4 m	4.1 m	4.4 m	4.5 m
1300 m	March 2001 post-processed	6	0.5 m	3.1 m	3.7 m	4.2 m	1.7 m	1.7 m
1300 m	October 2000 post-processed	11	2.7 m	4.0 m	1.2 m	1.7 m	1.7 m	1.7 m

Table 4: Position accuracy

Besides improving the position accuracy, another reason for equipping the HUGIN vehicles with INS was to decrease the reliance on DGPS-HiPAP. This has been very successful. Not only does the INS provide gapfilling when the HiPAP-system loses track, but in certain autonomous operations it has made it possible to run without HiPAP for a few hours. In area mapping the vehicle will typically follow a 'lawnmower' pattern, a series of reciprocal headings that gives complete coverage of the area. These reciprocal headings limit the increase of position error and keeps position accuracy within the requirements for at least some time-limited applications. An example from a run in 200 m water depth is shown in Figure 6.

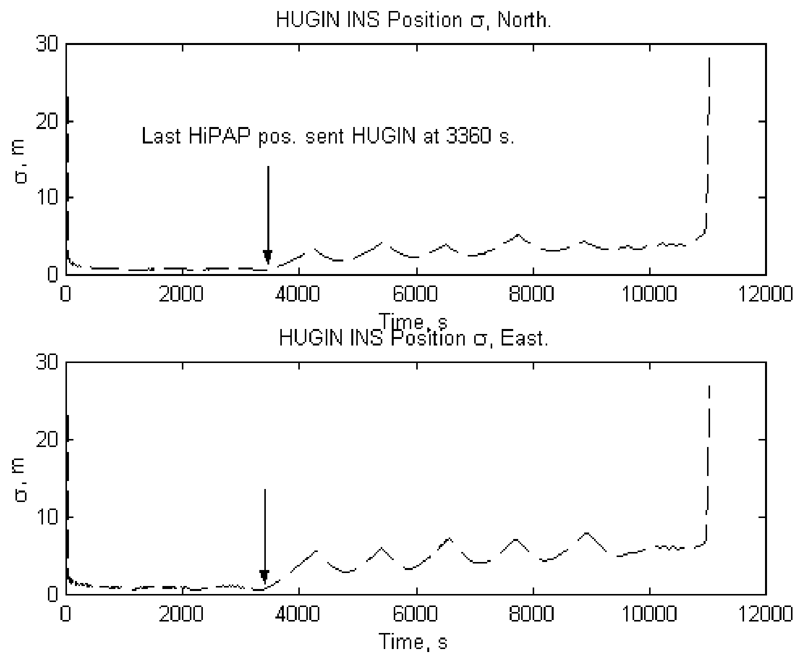

Figure 6: Position accuracy without HiPAP. At time t = 11000 s DVL bottom track is lost

8. Summary

Alternative ways of integrating time delayed DGPS-SSBL measurements with inertial navigation have been discussed and the method chosen for the HUGIN 3000 navigation system presented.

The HUGIN 3000 navigation system has proved robust, stable and accurate performance in sea trials carried out in deep water in the Gulf of Mexico.

9. Acknowledgement

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