MANEUVERING VEHICLE LOCALIZATION WITH AN ACOUSTIC LONG BASELINE SYSTEM

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1 Introduction

The localization error of the long baseline (LBL) acoustic localization system is sensitive to vehicle motion between the time the vehicle sends out an interrogation signal and the times of receptions for the acoustic replies from the various transponders. The static-vehicle model (SM) for localization does not take vehicle motion into consideration and calculate the one-way acoustic travel time from the vehicle to a transponder by halving the observed two-way traveltime from vehicle to the transponder and back. This is the reason why esult larger localization errors for a maneuvering vehicle are obtained in an actual LBL trial than the posterior uncertainty estimated by the posterior covariance matrix of the static localization model.

To address this problem, in this paper, we tried to use time corrections as additional unknown parameters estimated via Bayesian inversion to reduce the localization errors related to vehicle motion by the SM, rather than using Kalman filters. In this extended SM, referred as motion-compensated model (MM), vehicle interrogation coordinates, transponder coordinates, and time corrections are all estimated using a strongly underdetermined linearized Bayesian inversion, given reasonable prior information. An LBL field trial indicated that this MM approach is effective in compensating the influence of vehicle motion.

2 Method

In the MM inversion algorithm, the dependence of vehicle location (x,y,z), transponder location (X,Y,Z) and the one-way travel-time t^{obs} calculated by simply half the observed two-way travel-time can be written as

$$t(x_i, y_i, z_i, X_j, Y_j, Z_j, c) + \Delta t_{ij} = t_{ij}^{\text{obs}}, \qquad (1)$$

where Δt is the travel-time correction, which compensates the signal travel-time difference of interrogation and reception. The sequence number of the localization cycle is marked as *i* and *j* represents different transponders. The synthetic halved two-way travel time *t* is calculated with interrogation location, transponder location and SSP *c* via ray tracing method. With local linearization and prior information $\hat{\mathbf{m}}$, the Bayesian inversion solution of Eq.(1) is expressed as

$$\mathbf{m} = \hat{\mathbf{m}} + \left(\mathbf{J}^{\mathrm{T}} \mathbf{C}_{D}^{-1} \mathbf{J} + \mathbf{C}_{M}^{-1} \right)^{-1} \mathbf{J}^{\mathrm{T}} \mathbf{C}_{D}^{-1} \left(\mathbf{d} - \mathbf{J} \hat{\mathbf{m}} \right), \quad (2)$$

where $\mathbf{m} = [x_i, y_i, z_i, X_j, Y_j, Z_j, \Delta t_{ij}]^T$ is the unknown model parameters vector in this problem. **J** represents the Jacobian matrix consisted by the partial derivatives of *t* with respect to $\mathbf{m} \cdot \mathbf{C}_D$ is the covariance matrix of the data, \mathbf{C}_M is the covariance matrix of the prior model. As this approach is based on linearization, it is repeated iteratively until convergence (when model changes between iterations become insignificant).

Larger quantity of unknown parameter than data leads to a strongly under-determined inversion, which is regularized by including prior estimates (with Gaussian uncertainties) for all parameters. The key to this algorithm is setting the prior estimates for the travel-time corrections. This is carried out by first estimating the vehicle locations at the time instants the interrogation signals are sent by applying cubic-spline interpolation of the results of an initial localization inversion assuming a static vehicle, and then determining the corresponding travel-times by ray tracing.

3 Results

3.1 Lake Trial Procedure

A LBL field trial was carried out on Nov. 3rd, 2014, in Songhua Lake, Jilin, China. The lake trial was aimed to test a LBL acoustic localization system designed for AUV



Figure 1: Components of the LBL system tested in the field trial, including transducer, transponder, computer, signal processing box and power box (counter-clockwise from top left)

Localization. The LBL system is composed of four transponders (T1 to T4), a transceiver transducer, a processing box and a power box, shown in Fig. 1. The acoustic transducer of the transceiver was firmly installed on the starboard side of the boat by a triangular-prism-shaped steel frame. On top of the fame, the antenna of a mobile GPS station was fastened and was set in the real time kinematic mode. A gyroscope was installed between the frame and the transducer to measure yaw, pitch and roll of the boat. With the data from GPS and gyroscope, the geodetic coordinates of the transducer can be calculated with better than 4 cm precision. These geodetic coordinates are logged as references to evaluate the localization error of acoustic localization.

Transponders were deployed on the lakebed at about 35 m depth and are localized by the array element acoustic survey (AEL) with about 4 cm precision. When the AEL survey was finished, motion vehicle survey (MVL) were conducted in which the boat was treated as a substitute for an AUV, and moved back and forth within an about 300 m \times 300 m area centered on the average of transponder coordinates. The geometry of the transponder array and the survey tracks are shown in Fig. 2(a).



Figure 2: (a) Motion vehicle survey track and transponder locations. (b) Localization error comparison between SM inversion and MM inversion.

3.2 Data Processing Results

The maneuvering surface boat is localized with two models: the static model (SM) that estimates vehicle and transponder locations ignoring vehicle motion; the motion-compensated model (MM) that estimates these locations and travel-time corrections. In this paper, localization errors in the trial are regarded as the difference between inversion results and the measured geodetic coordinates of the transducer.

The localization error curves versus time are shown in Fig. 2(b). The error of SM method varies invensively. The largest localization error is almost 1 m. Generally, large localization errors correspond to places where the boat is outside the transponder array. When the vehicle was inside the array, the maximum localization error is about 50 cm and the averaged error is 19 ± 14 cm, which is significant larger than the expected 4 cm uncertainty estimated from the posterior matrix. In the motion-compensated inversion, the average localization error is 3.4 ± 1.4 cm when the vehicle was inside the transponder array. Even when the vehicle moved outside the array, the error is still generally less than 20 cm. Therefore, the data processing results indicate that the MM method is helpful in compensate the localization error generated by vehicle motion.

4 Conclusion

This paper describes the compensation for vehicle motion during the interrogation-reception time interval between the vehicle and transponders in a long baseline (LBL) system lake trial without using Kalman filter. This compensation method is base on Bayesian inversion algorithm which includes travel-time corrections as additional unknown parameters with prior determined by interpolating the vehicle location at interrogation time instants using staticvehicle localization model (SM) results. Field trials results showed that the motion-compensated inversion (MM) reduced averaged acoustic localization errors of a surface vehicle to 3.4 ± 1.4 cm, much accurate than the 19 ± 14 cm error for the static inversion.

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