Log Sensor Calibration Using M-estimate

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Abstract- **A calibration problem for log sensor of UUV is established and the problem can be divided into two separate parts: misalignment angle and scale factor of log sensor. Instead of using the conventional least square algorithm, a fine calibration approach based on M-estimate is used to suppress the effect of non-white noise. The adaptive factor relation to calibration precision is brought forward which is different from usual forgetting factor. The feasibility of the approach is demonstrated in the test of sea trail.**

I. INTRODUCTION

The log sensor has to be calibrated with respect to compass prior to being used if a log sensor is used in UUV (Unmanned Underwater Vehicle). The calibration is for navigation aiding with optimal performance. Usual calibration algorithm is least square estimation method (LSE) [1]. It is valid under white noise. However, the sensor data are commonly not consistent with the nominal model assumption. In fact, GPS position errors are non-white because they are determined by pseudo-range measurements and satellite geometry with respect to GPS receiver's site [2]. Further more, the GPS outputs may be disturbed by impulse noise due to unknown environments. Under many such adverse conditions, the performance of the linear filters deteriorates significantly. For example, LSE algorithm performs badly under impulse noise if lack of enough data. It is necessary to fetch a useful algorithm with good robustness for log sensor calibration. M-estimate may be a favorable alternative to satisfy the need because of impulse noise suppression [3]. A recursive M-estimate is proposed with required threshold parameters estimation [4].Extensive simulations showed M-estimate is effective under impulse noise environment. The M-estimate in [4] uses a forgetting factor enhancing newcome inputs to weight the cost function. The factor is chosen intuitively with some random. We give a determined factor with respect to distance UUV sailed. The factor is adopted in the algorithm to determine the weights instead of forgetting factor. The log sensor calibration method based on M-estimate algorithm proposed is considered in this paper.

II. PROBLEM FORMULATION

The speed received by UUV for navigation in the log sensor reference frame is different from that in the compass frame. Therefore it is necessary to calibrate the log sensor with respect to compass before it is used for navigation of UUV. UUV reference frame is defined by axis x_b, y_b and z_b (see Fig.1), where x_b -is in the UUV horizontal plane, pointing to bow; y_b -is in the UUV horizontal plane, pointing to starboard; z_b -is in the perpendicular to UUV horizontal plane, pointing upward. Angles R_s, P_s, H_s show the misalignment between log sensor main axis (x_s,y_s,z_s) and compass main axis (x_c,y_c,z_c), not the one between UUV reference main axis and log sensor main axis or compass main axis. The roll and pitch misalignment angles R_s, P_s measure the lack of parallelism

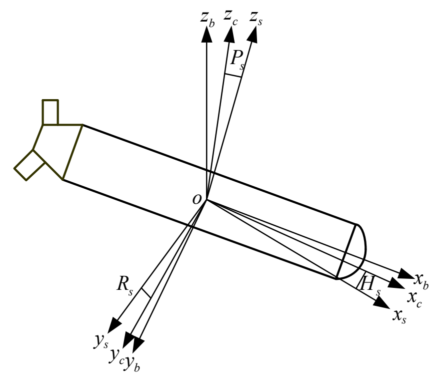

Figure 1. Three reference frame in UUV

between compass horizontal plane and log sensor horizontal plane. Generally, their value can be kept to the default value zero as long as they do not exceed several degrees. Therefore we mainly care about the heading misalignment angle H_s ranger than roll and pitch misalignment angle. Scale factor δ (in units of %) accounts for compensation of log sensor measurement uncertainty. The scale factor is mainly related to the sensor itself. Since heading misalignment angle H_s is also small, the transformation equation between the compass and the log sensor reference frame is given as below [5].

$$C_s^c = \begin{bmatrix} 1 & H_s & -P_s \\ -H_s & 1 & R_s \\ -P_s & -R_s & 1 \end{bmatrix} \approx \begin{bmatrix} 1 & H_s & 0 \\ -H_s & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{1}$$

The rotation order of transformation from compass reference frame to geographical frame is defined as roll first, pitch followed, heading last. Then the transformation is given by

$$C_c^g = \begin{bmatrix} \mathrm{c}\gamma\mathrm{c}\psi + \mathrm{s}\gamma\mathrm{s}\psi\mathrm{s}\theta & \mathrm{s}\psi\mathrm{c}\theta & \mathrm{s}\gamma\mathrm{c}\psi - \mathrm{c}\gamma\mathrm{s}\psi\mathrm{s}\theta \\ -\mathrm{c}\gamma\mathrm{s}\psi + \mathrm{s}\gamma\mathrm{c}\psi\mathrm{s}\theta & \mathrm{c}\psi\mathrm{c}\theta & -\mathrm{s}\gamma\sin\psi - \mathrm{c}\gamma\cos\psi\mathrm{s}\theta \\ -\mathrm{s}\gamma\mathrm{c}\theta & \mathrm{s}\theta & \mathrm{c}\gamma\mathrm{c}\theta \end{bmatrix} \tag{2}$$

where c denotes cosine, and s denotes sine, ψ , θ and γ denotes the heading, pitch and roll angle.

Assuming that both the origins of compass reference frame and the log sensor reference frame are at the same point, the

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speed in geographical frame can be obtained from (1)and(2) by the following transformation

$$\boldsymbol{V}^g = \delta \cdot C_c^g C_s^c \boldsymbol{V}^s \tag{3}$$

where

$\boldsymbol{V}^s = [V_x^s \quad V_y^s \quad V_z^s]'$ represents speed vector in the log sensor reference frame;

$\boldsymbol{V}^g = [V_e^g \quad V_n^g \quad V_u^g]'$ represents speed vector in the geographical frame, and the superscript denotes the frame, subscript denotes the axis.

The eastern and northern speed parts is obtained from (3)

$$\begin{cases} V_e^g = \delta \cdot (V_e^{g'} + H_s \cdot V_n^{g'}) \\ V_n^g = \delta \cdot (V_n^{g'} - H_s \cdot V_e^{g'}) \end{cases} \tag{4}$$

where

$$\begin{cases} V_e^{g'} = C_c^g(1,1)V_x^s + C_c^g(1,2)V_y^s + C_c^g(1,3)V_z^s \\ V_n^{g'} = C_c^g(2,1)V_x^s + C_c^g(2,2)V_y^s + C_c^g(2,3)V_z^s \end{cases} \tag{5}$$

The eastern and northern distance at the time k through dead reckon calculations are given as follows

$$\begin{cases} \Delta E(k) = \delta \sum_{i=1}^{k} [V_e^{g'}(i) + H_s \cdot V_n^{g'}(i)] \cdot \Delta T \\ \Delta N(k) = \delta \sum_{i=1}^{k} [V_n^{g'}(i) - H_s \cdot V_e^{g'}(i)] \cdot \Delta T \end{cases} \tag{6}$$

where ΔE and ΔN respectively denotes the distance UUV sailing in east and north, ΔT represents the sampling interval.

UUV is connected to a GPS receiver and receive real-time valid GPS fixes during log sensor calibration. The sailing distance calculation is given as below by GPS fixes in WG-84 geographical frame

$$\begin{cases} \Delta E(k) = \sum_{i=1}^{k} [\lambda(i) - \lambda(i-1)] \cdot R_M \cos(L(i-1)) \\ \Delta N(k) = \sum_{i=1}^{k} [L(i) - L(i-1)] \cdot R_N \end{cases} \tag{7}$$

where

R_M, R_N - the radii of curvature of the reference ellipsoid in Prime Meridian and Vertical Meridian, respectively[5];

λ, L -longitude and latitude received from GPS, respectively. Then the following formula can be educed by modification of (7).

$$Vse(k) / Vsn(k) = \Delta E(k) / \Delta N(k) \tag{8}$$

where

$$Vse(k) = \sum_{i=1}^{k} [V_e^{g'}(i) + H_s \cdot V_n^{g'}(i)]$$

$$Vsn(k) = \sum_{i=1}^{k} [V_n^{g'}(i) - H_s \cdot V_e^{g'}(i)]$$

The scale factor δ has been eliminated in (8). The value of $\Delta E(n)$ and $\Delta N(n)$ are derived from (7). Therefore the misalignment angle H_s can be acquired.

After the misalignment angle H_s has been solved, we put the angle into (6). The δ can be solved from one of the two distance equations, which distance is longer.

III. ROBUST M-ESTIMATE TO CALIBRATION

The log sensor calibration problem is formulated above. Equation (8) with multiple dimensions can be rewritten as an linear filter

$$\boldsymbol{y}(k) = \boldsymbol{x}(k) H_s(k) + \boldsymbol{e}(k) \tag{9}$$

where $\boldsymbol{e}(k)$ denotes the estimation error. In the conventional least-squares filter, the cost function is expressed as $J_n(H_s) = \sum_{i=1}^{n} \beta^{n-i} e_i^2(k)$, where $0 < \beta \leq 1$ is the forgetting factor and n is the dimension of $\boldsymbol{y}(k)$ in (9). The log sensor calibration accuracy is in relation to sailed distance. The accuracy of the heading misalignment estimation can be considered as

$$\Delta H_s = \Delta_{GPS} / D \tag{10}$$

This means that precision becomes higher when the distance UUV moving is longer. Instead of using conventional forgetting factor which is chosen by handwork in [4], the following adaptive adjusting factor based on the mutative estimation precision is proposed

$$\alpha(k) = D(k) / D_{final} \tag{11}$$

where D_{final} denotes the final distance, $D(k)$ denotes the nth distance. In the light of robustness concepts, the log sensor calibration problem can be solved in a resistance and efficiency robust manner. This can be done using the M-estimate, which is defined as the minimization problem with some difference from [4] and [4].

$$\hat{H}_s(k) = \arg\min_{H_s} J_n(H_s) \quad J_n(H_s) = \sum_{i=1}^{n} \alpha_i(k) \rho(e_i(k)) \tag{12}$$

where $\rho(\cdot)$ is a M-estimate function to cut off outliers, Particularly, if it is a quadratic function, the estimate (12) reduces to the conventional least squares filter solution. This algorithm is optimal when the underlying Gaussian noise. However, due to the existence of some outliers, the real noise for large samples is no longer Gaussian. The resistant robustness of the cost function is required. It can be chosen as the modified Huber M-estimate function or other M-estimate function. The more general Hample's three-parts-redescending M-estimate function $\rho(\cdot)$ illustrated is considered in [4]. It becomes apparent that the M-estimator is capable of suppressing non-white noise such as impulse with large amplitude from [4]. The threshold parameters are usually chosen according to the applications or estimated continuously. The optimal estimate can be obtained by setting the first partial derivative of $J_n(H_s)$ in (12), with respect to $H_s(k)$, to zero. This yields

$$\sum_{i=1}^{n} x_i(k) \alpha_i(k) \psi(e_i(k)) = \sum_{i=1}^{n} x_i(k) \alpha_i(k) q(e_i(k)) e_i(k) = 0 \tag{13}$$

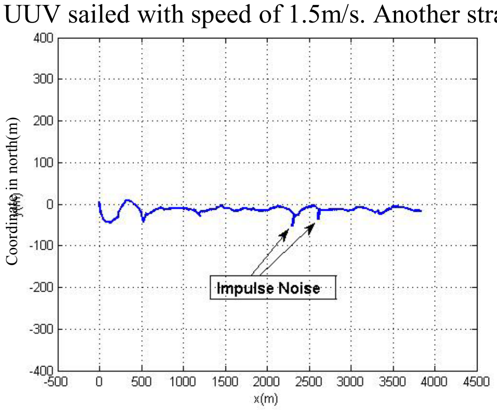
where $\psi(e) = \partial\rho(e) / \partial e$ and $q(e) = \psi(e) / e$ are called the score and weighting function, respectively. The weighting function $q(\cdot)$ is nonlinear [4] and the solution of (13) is difficult to solve. A weighted least square approximation for (13) can be obtained from [4]. The solution of (13) can be expressed as a weighted least square estimation

$$H_s(k) = ((\boldsymbol{x}(k)\boldsymbol{\alpha}(k))^T \boldsymbol{\Omega}(k-1)(\boldsymbol{x}(k)\boldsymbol{\alpha}(k)))^{-1}(\boldsymbol{x}(k)\boldsymbol{\alpha}(k))^T \boldsymbol{\Omega}(k-1)\boldsymbol{y}(k) \tag{14}$$

where $\boldsymbol{\Omega}(k-1) = diag\{\omega_1(k-1),...,\omega_n(k-1)\}$ is a diagonal matrix with weighted values of number n, and $\boldsymbol{\alpha}(k) = diag\{\alpha_1(k),...,\alpha_n(k)\}$. Reference [4] has proposed a robustified Kalman filter algorithm for (14). The calibration process can be divided into two separate parts according to our analysis: misalignment angle and scale factor of log sensor. The scale factor of log sensor can be estimated from (6) after H_s has been estimated. The calibration process is recursive and stopped when both parameters are stabilized, with the following criteria: variation of heading misalignment angle H_s lower than $\Delta H_s / 2$ in (10).

IV. TEST RESULTS FOR COMPARISON

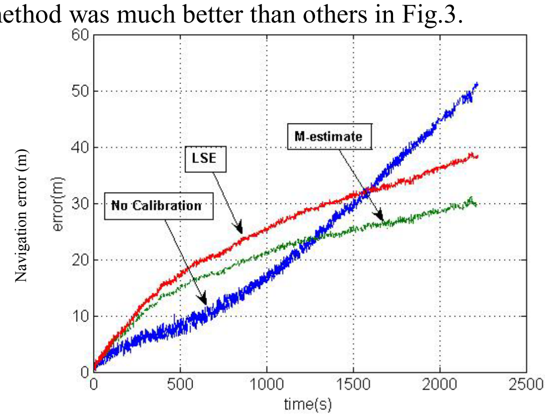
The proposed algorithm was applied in a sea trial. Our UUV uses DVL (Doppler Velocity Sensor) as log sensor. A low precision compass was employed as heading sensor. Here the M-estimate algorithm presented above was used with the experiment data to estimate the parameters. We chose a straight line for 3800m as common testing track of the three calibration methods, no calibration, LSE and M-estimate. The measured coordinates were corrupted by impulse noises in Fig.2. UUV sailed with speed of 1.5m/s. Another straight line



Coordinate in east (m)

Figure 2. Calibration track with impulse noise

was chosen arbitrarily as test track for comparison. The navigation errors were the differences between GPS fixes and UUV's position in the track. The performance of M-estimate method was much better than others in Fig.3.



Time (s)

Figure 3. Navigation errors of three methods

The results obtained in both the same test track and calibration track are shown in TABLE I. The accuracy is defined as a ratio of navigation errors at the end of tack to the total length of test track, denoted by 'D'. M-estimate method is obviously robust with better navigation accuracy than others. The position error of our GPS receiver is about 15m. Consequently, the accuracy of the misalignment angle H_s is round 0.20° according to (10).

TABLE I

Comparison of three method on accuracies

Method	H_s (°)	δ (%)	Accuracy (%D)
None	/	1	1.483
LSE	1.39	1.0070	1.103
M-estimate	1.18	1.0105	0.862

V. CONCLUSION

A calibration approach for misalignment angle and scale factor of log sensor in UUV with measurements from natural GPS has been presented. The approach is based on M-estimate estimation theory: not only of robustness, but also resistive to bad data. Performance comparison of test trial showed the validity. It is believed that the proposed approach represents a favorable in-the-field alternative to calibration of log sensor. Test results shows it is imperative to exactly estimate the value of log sensor parameters.

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