Sensor Bias Correction in Simultaneous Localization and Mapping

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Abstract —*The imprecision of sensor measurements due to systematic and nonsystematic errors can give rise to severe problems in several autonomous navigation tasks. In particular, the errors due to sensor bias can render existing Simultaneous Localization and Map Building (SLAM) algorithms useless as such biases cause the estimators to diverge. This paper describes a method to estimate and compensate these ever present and particularly cumbersome sensor and input biases in real time in the context of SLAM applications without an a priori map of the environment. The validity of the proposed methodology is verified via simulations for the case of an autonomous land vehicle navigating in a completely unknown 2D terrain. It is assumed that biased and noisy range and bearing measurements to point landmarks are obtainable in real-time, using a sensor such as a laser scanner.*

Keywords: SLAM, tracking, filtering, estimation, map building, localization, robotics.

1 Introduction

The problem of localization and map building has often been recognized as one of the major problems of autonomous vehicle navigation in robotics literature. It is also perceived that the capability of simultaneous self-localization and map building without an a priori map would make a robot truly autonomous. The SLAM problem examines whether a vehicle in an unknown environment starting from an unknown location can build a map of its environment incrementally whilst simultaneously using the map to localize and navigate in real time. The first true solution to the simultaneous localization and mapping problem was due to Smith, Self and Cheeseman [1], They cast the problem in a stochastic framework and used an extended Kalman filtering (EKF) approach to estimate the landmark positions and vehicle pose. The major highlight of the formulation was its consistent probabilistic representation of robot's pose, and landmark position uncertainties and their relationships. The methodology is still considered to be the primary framework of most feature based stochastic SLAM algorithms. This was followed by the work of Mourtarlier

and Chatila [2] and work on visual navigation by Ayache and Faugerras [3]. Since then, several other alternative approaches have been proposed, which include the occupancy grid based localization [4] and the more recent probabilistic and particle filter based methods [5], [6] and [7].

In this paper, the feature based approach to SLAM set within an EKF/stochastic framework is used for sensor and input bias estimation and compensation. Success of the approach to the SLAM depends on how well the dependencies or correlations among map elements and the vehicle are considered. Although, within the stochastic mapping framework, the EKF based estimation has gained much popularity in the SLAM research community, it poses several shortcomings. Major shortcomings of an EKF based SLAM approach are its susceptibility to data association errors and inconsistent treatment of nonlinearities. Further, the propagation of sensor uncertainties due to systematic biases and random errors accentuate the problems and often results in an inconsistent and inaccurate map. As more and more feature measurements are taken and used to update the map and vehicle pose estimates, bias errors tend to spread across the entire map resulting in a false and inconsistent map. Another major shortcoming of the approach is the computational complexity (storage and time) due to the requirement of maintaining of all correlations (map elements and vehicle) explicitly in the state vector covariance matrix. However several researchers have addressed this issue in various ways [8], [9] and [10] and therefore not considered in this work.

There are several reasons for nonlinearity and bias related uncertainty propagation in the stochastic mapping framework [11]. Nonlinear transformations in the EKF cause the Gaussian assumptions in measurement and process noise invalid, biased or underestimated. Another reason is the violation of linear assumptions in the first order approximations by Taylor series expansion if the measurement and vehicle process noise is large. Persistent biases that exist due to modeling errors, sensor biases and calibration errors also contribute to map divergence and errors. In small-scale SLAM implementations, it has been shown that by adding more stabilizing process and measurement noise the modeling errors and non-linearity

151

in state and measurement equations can be offset [13] and [14]. However, this will not always ensure consistent results in the presence of large sensor and control input biases, which are inevitably present in practical situations. Thus, bias and modeling offsets [11],[14] and their cumulative effects cause significant problems in large-scale outdoor SLAM applications. This paper proposes a methodology to explicitly account for the sensor biases in the measurements and control input offsets, in the context of EKF/SLAM so as to obtain consistent and accurate results for the map and vehicle pose.

The paper is organized in the following manner. In section 2, the process and observation models are formulated and the feature based stochastic SLAM framework employing an estimation theoretic EKF is summarized. In section 3, the EKF/SLAM formulation described in section 2 is modified to explicitly account for input and sensor biases within the same EKF/stochastic framework. This is followed by a discussion of issues of observability. In section 4 simulation results are shown to verify the effectiveness of the proposed methodology. Finally in section 5, the work is summarized with concluding remarks.
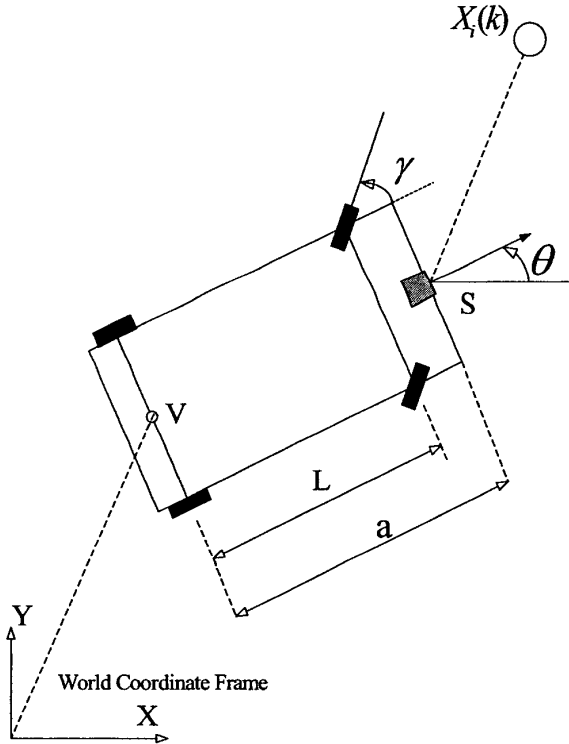

Figure 1-Vehicle and world coordinate frame

2 EKF Based Stochastic Mapping

The basic framework used in the EKF based SLAM algorithms represent both the vehicle and landmark locations by absolute coordinates with reference to some reference world coordinate frame {W}. The origin of this frame can be arbitrarily chosen and usually it is the initial position of the vehicle. The vehicle and measurement models are in general nonlinear.

2.1 Process and Observation Models

The process model comprises of the vehicle's kinematic model, and the landmark model.

Vehicle model

For the vehicle shown in Figure 1, the kinematic motion model is given by the nonlinear equations;

$$X_v(k+1) = F(X_v(k), U(k), u_n(k)) + v(k) \qquad (1)$$

$$F(X_v(k), U(k)) = \begin{bmatrix} x(k) + \Delta t u(k)\cos(\theta(k)) \\ y(k) + \Delta t u(k)\sin(\theta(k)) \\ \theta(k) + \dfrac{\Delta t u(k)\tan(\gamma(k))}{L} \end{bmatrix} \qquad (2)$$

The vehicle pose estimate at time k is given by $X_v(k) = [x(k) \ \ y(k) \ \ \theta(k)]^T$ where the vehicle position and orientation at time k are denoted by $(x(k), y(k))$ and $\theta(k)$ respectively.

$U(k) = [u(k) \ \ \gamma(k)]^T$, $u_n(k) \sim N(O, Q_1(k))$

and $v(k) \sim N(O, Q_2(k))$ are the control input, its additive noise and additive process noise respectively. L is the vehicle wheel base. Hence, the overall process noise covariance of the vehicle kinematic model is;

$$Q(k) = \left(\frac{\partial F(x,y,\theta)}{\partial U}\right) Q_1(k) \left(\frac{\partial F(x,y,\theta)}{\partial U}\right)^T + Q_2(k) \qquad (3)$$

Map model

Point landmarks (features) in the environment are represented by their position vectors, $X_i^L = (x_i^L, y_i^L)^T$ $(i=1,...n)$ with respect to the world frame. Since the landmarks are assumed stationary the model of a landmark, i, is;

152

$$X_i^L(k+1) = X_i^L(k) = \begin{bmatrix} x_i^L(k) \\ y_i^L(k) \end{bmatrix} \qquad (4)$$

Since the map is a collection of n landmarks, the vector representing its state $X_m(k)$ is;

$$X_m(k) = [X_1^L(k), \cdots \ X_i^L(k), \cdots \ X_i^L(k)]^T \qquad (5)$$

And hence, the state transition model of the map vector is;

$$X_m(k+1) = X_m(k) \qquad (6)$$

Overall process model

The overall process comprises of the vehicle kinematic model and the map model. Thus the overall state vector $X(k)$, is formed by concatenating the vehicle state with the map state as follows;

$$X(k) = \begin{bmatrix} X_v(k) \\ X_m(k) \end{bmatrix} \qquad (7)$$

It may be noted that the process state model evolves as given by equations (2) and (4).

Observation model

From figure 1 it follows that the absolute position of the sensor, $S = (x_s(k), y_s(k))$ at time k is given by ;

$$\begin{bmatrix} x_S(k) \\ y_S(k) \end{bmatrix} = \begin{bmatrix} x(k) + a\cos(\theta(k)) \\ y(k) + a\sin(\theta(k)) \end{bmatrix} \qquad (8)$$

It is assumed that the sensor measures, in its field of view, the range, $r(k)$, and bearing, $\alpha(k)$, to a point target (landmark). Thus the measurement model for the ith landmark, $X_i^L(k) = (x_i^L(k), y_i^L(k))^T$, with respect to the vehicle coordinate frame {V} is :

$$Z(k) = \begin{bmatrix} r(k) \\ \alpha(k) \end{bmatrix} = h(X_v(k), x_i^L(k), y_i^L(k)) + w(k) \qquad (9)$$

$$= \begin{bmatrix} \sqrt{(x_i^L(k) - x_S(k))^2 + (y_i^L(k) - y_S(k))^2} \\ \tan^{-1}\left(\dfrac{y_i^L(k) - y_S(k)}{x_i^L(k) - x_S(k)}\right) + \dfrac{\pi}{2} - \theta(k) \end{bmatrix} + w(k) \qquad (10)$$

where the measurement noise sequence, $w(k)$ is given by $w(k) \sim N(O, R(k))$ and it is temporally uncorrelated with the process noise.

2.2 Algorithm outline

Landmark tracks are initiated, maintained and deleted according to the method outlined in [12]. The method keeps two lists; one for confirmed landmark tracks and the other for tentative landmark tracks. At the beginning of the map building process, both lists are initialized to null. Whenever a new candidate landmark is detected it is checked with the landmarks of the confirmed and tentative lists. If the candidate landmark observation does not associate with any confirmed or tentative landmarks, it is most probably a new landmark and hence added to the tentative list. If it is associated with a tentative landmark, it is used to update the particular tentative landmark. If it is associated with a confirmed landmark, it is used to update the augmented process state vector (which includes the map and vehicle state) and its covariance according to the EKF update equations. Sufficiently stable landmark tracks observed over a period are moved to the confirmed landmark list. A nearest neighbor data association filter is used for association of a landmark observation to a previously observed landmark. A measure of quality is determined for the confirmed landmarks based on the probability density function of the observation innovations of observation to track associations. Those tracks that do not achieve a pre set value of landmark quality are deleted from the confirmed landmark list and hence the map state vector.

2.3 Map building and localization

EKF equations used for map building and vehicle state estimation are summarized below. The overall state vector comprising the vehicle and map states is given in equation (7). At each sampling time, measurements associated with the confirmed landmarks are used to update the state vector according to the usual predictor corrector form of the extended Kalman filter. The state vector prediction and covariance prediction is implemented using the following equations.

$$X(k+1 \mid k) = \begin{bmatrix} X_v(k+1 \mid k) \\ X_m(k+1 \mid k) \end{bmatrix} \qquad (11)$$

$$X_v(k+1 \mid k) = F(X_v(k \mid k), U(k)) \qquad (12)$$

$$X_m(k+1 \mid k) = X_m(k) \qquad (13)$$

$$P(k+1 \mid k) = AP(k \mid k)A^T + Q_{aug}(k) \qquad (14)$$

Where the Jacobian $A = \begin{bmatrix} \dfrac{\partial F(x,y,\theta)}{\partial(x,y,\theta)} & O_{3x2n} \\ \hline O^T_{3x2n} & I_{2nx2n} \end{bmatrix}$, and

the matrices, and O_{3x2n} and I_{2nx2n} are 3x2n null matrix

and a 2nx2n identity matrix. Jacobian $\dfrac{\partial F(x,y,\theta)}{\partial(x,y,\theta)}$ is

evaluated at every sampling instant for the estimated vehicle state at time k. When O_{2nx2n} is a 2nx2n null matrix, Q_{aug}, is given by;

$$Q_{aug} = \begin{bmatrix} Q(k) & O_{3x2n} \\ \hline O^T_{3x2n} & O_{2nx2n} \end{bmatrix}$$

The predicted measurement and the measurement Jacobian, H for the ith landmark can be evaluated as follows;

$$Z(k+1 \mid k) = h(X_v(k+1 \mid k), x_i(k \mid k), y_i(k \mid k)) \quad (15)$$

$$H = \begin{bmatrix} \dfrac{\partial r}{\partial X_v(x,y,\theta)} & 0....0 & \dfrac{\partial r}{\partial x_i} & \dfrac{\partial r}{\partial y_i} & 0.....0 \\ \dfrac{\partial \alpha}{\partial X_v(x,y,\theta)} & 0....0 & \dfrac{\partial \alpha}{\partial x_i} & \dfrac{\partial \alpha}{\partial y_i} & 0.....0 \end{bmatrix} \quad (16)$$

If the true measurement is Z(k+1), the innovation is v(k+1), its covariance S(k+1) and the Kalman gain is W(k+1), the update equations for the map augmented state vector and its covariance matrix are given by;

$$v(k+1) = Z(k+1) - Z(k+1 \mid k) \quad (17)$$

$$S(k+1) = HP(k+1 \mid k)H^T + R(k+1) \quad (18)$$

$$W(k+1) = P(k+1 \mid k)H^T S^{-1}(k+1) \quad (19)$$

$$X(k+1 \mid k+1) = X(k+1 \mid k) + W(k+1)v(k+1) \quad (20)$$

$$P(k+1 \mid k+1) = P(k+1 \mid k) - W(k+1)S(k+1)W^T(k+1) \quad (21)$$

The above set of equations is used to update the vehicle location and the feature map simultaneously with their uncertainties.

3 Sensor and input bias estimation

Work by Clark [13] and Williams [14] are some example of earlier successful attempts to estimate vehicle parameters and input biases in the context of SLAM. Here, a rigorous framework is formulated for estimating all biases, including the vehicle inputs and sensor biases in a consistent manner. In [15] Bar-Shalom notes that, in target tracking radar systems using moving platforms where the platforms' location estimates obtained from GPS are subject to slowly varying biases, and there are no fixed known targets to estimate their biases, the next best alternative is to use targets of opportunity at fixed but unknown locations. It is also noted that under certain observability conditions these biases can be estimated. This idea is further extended by the work of Okkello [16] for radar bias estimation, joint registration and track-to-track fusion based on measurement estimates generated by geographically separated radar trackers. Our approach inspired by the above work[15] and [16] by using the unknown, fixed landmark location estimates obtained by the uncertain measurements obtained by the biased sensors whose locations are also uncertain to estimate the sensor intrinsic bias parameters and the vehicle input biases.

3.1 Problem Formulation

In this section it is shown how any bias in a sensor(s) and the control input(s) can be estimated and compensated for, in the context of SLAM. For simplicity the derivation is given for a single sensor with range and bearing biases, together with control input biases, without losing the generality of including many sensors. Let the stacked constant biases in the input vehicle velocity, and steering angle be $u_b(k)$, and $\gamma_b(k)$, respectively. Should these bias parameters be time varying it is straightforward to model their time varying characteristics in the given formulation. Suppose, the single sensor's (possibly a laser scanner) biases in the range and bearing be $r_b(k)$ and $\alpha_b(k)$ respectively.

Process model with bias

A vector of biases, $X_b(k)$, is formed incorporating all the biases as shown in equation (22).

$$X_b(k) = [u_b(k) \ \gamma_b(k) \ r_b(k) \ \alpha_b(k)]^T \quad (22)$$

Now the overall process state is augmented to include the bias vector $X_b(k)$, as follows:

154

$$X(k) = \begin{bmatrix} X_v(k) \\ X_b(k) \\ X_m(k) \end{bmatrix} \qquad (23)$$

Equations (1) through (21) are modified appropriately as required to reflect the new overall state vector that include the unknown biases. The resulting modified process state equations are given in equations (24) to (27).

$$X_v(k+1 \mid k) = F(X_v(k \mid k), U(k) + U_{bias}(k \mid k)) \quad (24)$$

where, $\qquad U_{bias}(k \mid k) = \begin{bmatrix} u_b(k \mid k) \\ \gamma_b(k \mid k) \end{bmatrix} \qquad (25)$

$$X(k+1 \mid k) = \begin{bmatrix} X_v(k+1 \mid k) \\ X_b(k \mid k) \\ X_m(k \mid k) \end{bmatrix} \qquad (26)$$

The state covariance prediction (14) is the same except its components are modified as;

$$Q_{aug} = \begin{bmatrix} Q(k) & \vdots & O_{3x(2n+4)} \\ \hdashline O^T_{3x(2n+4)} & \vdots & O_{(2n+4)x(2n+4)} \end{bmatrix} \text{ where }$$

$O_{3x(2n+4)}$, is a 3x(2n+4) null matrix, $O_{(2n+4)x(2n+4)}$ is a (2n+4)x(2n+4) null matrix and the Jacobian A is given by;

$$A = \begin{bmatrix} \dfrac{\partial G}{\partial(x,y,\theta)} & \vdots & \dfrac{\partial G}{\partial(u_b,\gamma_b)} & \vdots & O_{3x(2n+2)} \\ \hdashline O_{2x3} & \vdots & I_{2x2} & \vdots & O_{2x(2n+2)} \\ \hdashline O^T_{3x(2n+2)} & \vdots & O_{(2n+2)x2} & \vdots & I_{(2n+2)x(2n+2)} \end{bmatrix}$$
$$(27)$$

and $\quad G = F(X_v(k \mid k), U(k) + U_{bias}(k \mid k)) \qquad (28)$

where, $O_{3x(2n+2)}$, O_{2x3}, $O_{2x(2n+2)}$ are size 3x(2n+2), 2x3 and 2x(2n+2) null matrices, $I_{(2n+2)x(2n+2)}$ is a (2n+2)x(2n+2) identity matrix. Similarly the Jacobian of the input noise given by (3) also has to be modified to account for the biases.

Measurement model including bias

Measurement model equations given by (8), (9) and (10) are appropriately modified to include the biases in the range and bearing measurements. Thus, the following measurment prediction equations result :

$$Z(k+1 \mid k) =$$
$$h(X_v(k+1 \mid k), x_i(k \mid k), y_i(k \mid k), X_b(k \mid k)) \quad (29)$$

Let $Z(k+1 \mid k) = \begin{bmatrix} z_1 & z_2 \end{bmatrix}^T$, then the new measurement Jacobian H, in the presence of biases when observing the ith landmark is;

$$H = \begin{bmatrix} \dfrac{\partial z_1}{\partial X_v(x,y,\theta)} 0\,0\,1\,0\,0....0 & \dfrac{\partial z_1}{\partial x_i} & \dfrac{\partial z_1}{\partial y_i} & 0.....0 \\ \dfrac{\partial z_2}{\partial X_v(x,y,\theta)} 0\,0\,0\,1\,0....0 & \dfrac{\partial z_2}{\partial x_i} & \dfrac{\partial z_2}{\partial y_i} & 0.....0 \end{bmatrix}$$
$$(30)$$

Prediction and update equations correspond to (17) to (21) with appropriate substitutions described above.

3.2 Observability Issues

The derived EKF/SLAM will only converge if all of the states are observable. By definition, information about an observable state is obtained from the observation equations. In the absence of this information, the filter estimate for that state will not simply converge to a meaningful solution. In general there are no specific rules governing the observability of nonlinear stochastic systems and therefore it is difficult to have prior judgements on the viability of EKF. However an observability test similar to those suitable for linear, time invariant systems may be carried out for nonlinear systems by linearising the observation model using Taylor series and examining the rank of the Jacobian of the observation model. In this case since there is only one state prediction *prior* for a set of many features, at first glance, it appears that the system is unobservable. Nevertheless, when more and more observations of the fixed landmarks are taken, it is possible to form a stacked measurement vector, resulting in a stacked Jacobian having the required minimum number of independent rows making its row rank equal to the dimension of the state vector. Hence in simple terms, provided an adequate number of observations satisfying the above conditions are available, the linearised system will be observable.

155

4 Simulation Results

Simulations, in an artificial unstructured environment (Figure 2) are conducted to show the importance of accounting for biases and the effectives of the proposed formulation for bias estimation to guarantee map convergence and vehicle localization. In figure 2 the artificial environment and the vehicle are shown. The symbol '.' denotes an actual landmark and the thick line denotes the actual path traversed by the vehicle. The thin line in the Figure 2 is the estimated vehicle path. A landmark's position estimate is shown by an 'x', together with its uncertainty ellipse (two sigma limits in the x and y directions). Estimated landmark locations and the vehicle path almost coincide with the true quantities in the figure. Gaussian noise and biases are added to the vehicle's control inputs, viz. speed and steering angle.
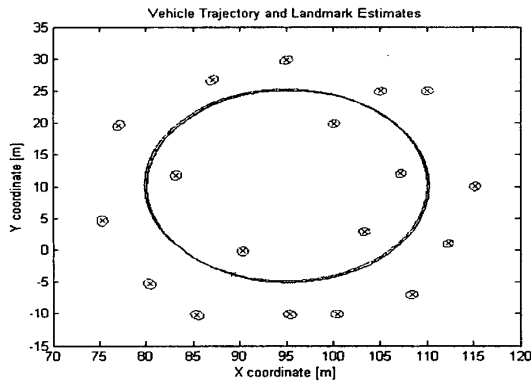
Figure 2 – Vehicle Trajectory and landmark estimates in SLAM with bias correction applied.

A range/bearing sensor (modeling a 2D laser scanner) with predefined uncertainty in range and bearing together with biases is used as the external landmark sensor. The exact bias values applied in the simulation are shown in table 1.

Table 1 – Parameters used in simulation

Parameter	Value
Speed input bias[m/s]	0.25
Steering angle input bias[degrees]	1.0
Sensor range bias[m]	0.5
Sensor bearing bias[degrees]	2.0

The vehicle's starting position is arbitrarily chosen with some known uncertainty. Landmarks are initialized and the data association performed as discussed in section 2. Figure 3 is obtained from the same SLAM algorithm run with the above biased sensors but without bias compensation aplied. The dashed lines show the three sigma limits and it is clear that the position error is out of the 99.74% confidence limits imposed by the three sigma limits. Figures 4, 5 and 6 show the vehicle position and

orientation estimation error plots. The dashed line is the one sigma limit, which clearly shows that the errors are bounded in the SLAM algorithm with the bias estimation incorporated. Figures 7, 8, 9 and 10 show the sensor bias estimates. It is clearly evident that bias parameters are being accurately determined. The results also indecate that there
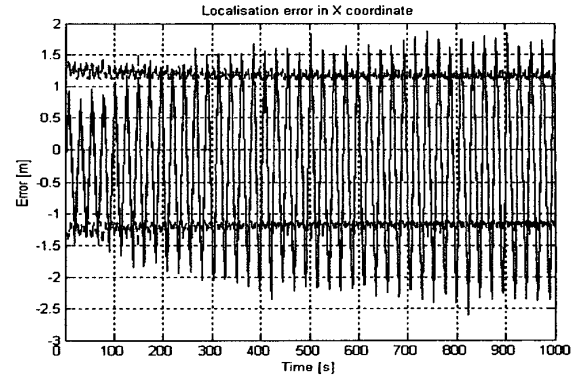
Figure 3 –Position error in localisation without bias correction applied
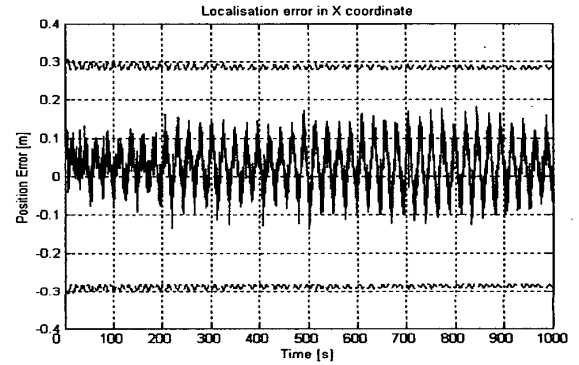
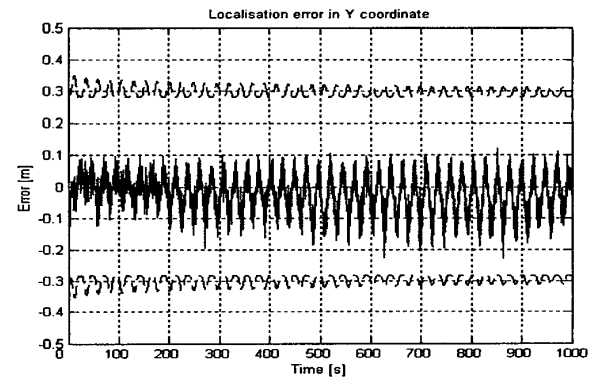Figure 4 - Vehicle x coordinate error in localisation with bias correction applied

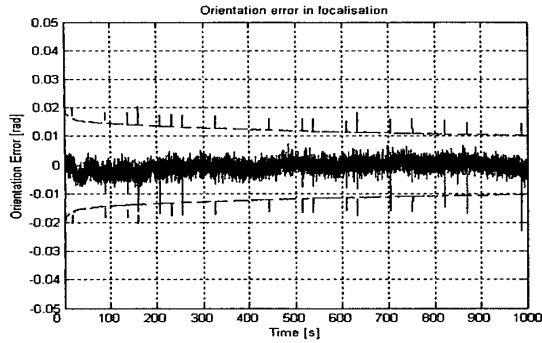Figure 5 - Vehicle y coordinate error in localisation with bias correction applied

156

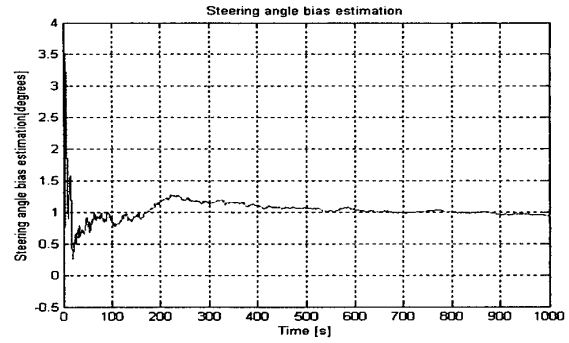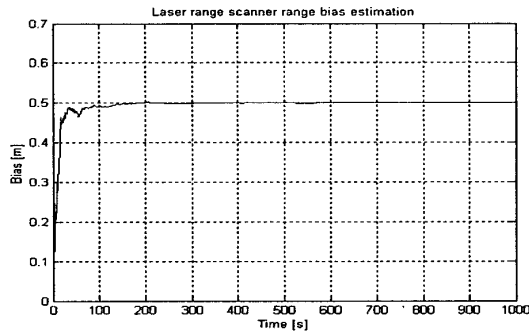Figure 6 – Vehicle orientation error in localisation with bias correction applied

Figure 7 –Laser scanner range bias estimation
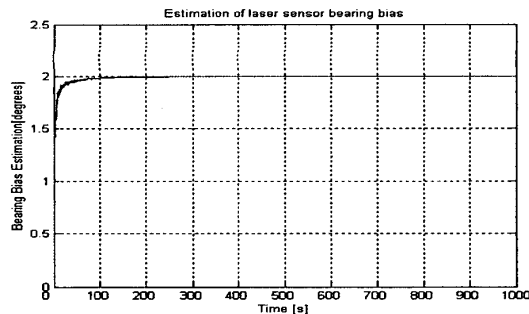

Figure 8 –Laser scanner bearing bias estimation
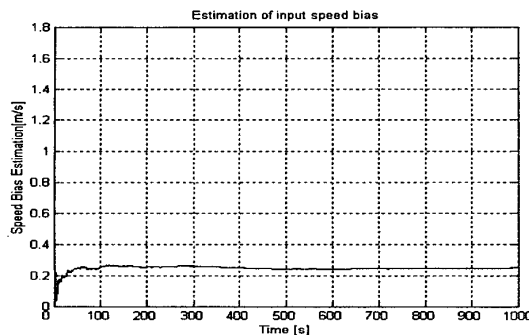

Figure 9 – Speed input bias estimation

Figure 10 – Steering angle input bias estimation

5. Conclusion and Future Work

The work carried out clearly shows that it is possible to estimate and compensate any sensor intrinsic parameters such as biases which are present in almost every practical SLAM application. Also it is evident that the estimation of these parameters is vital for consistency of map and its convergence and hence meaningful vehicle localization. Moreover the modification for bias compensation adds reasonably little computational overhead to the existing EKF based SLAM algorithms and is also applicable to almost anyother SLAM formulation such as the computationlly efficient approaches given in [7], [8] and [9]. The approach however is somewhat sensitive to the data association which is intrinsic to almost every EKF based estimator. The nearest neighbor data association filter is not appropriate for more complex, cluttered real time environments. It is therefore suggested that a more robust approach such as multiple hypotheses tracking be employed in actual practice. Future work will address the issues such as more robust data association methods, determining optimal path configurations, most informative landmark observations and sensor configurations that minimize the sensor biases, faults and other errors in SLAM algorithms and improving the overall efficiency of fully deployable SLAM implementations.

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157

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