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Sensor Fusion for Vehicle Positioning in Intersection Active Safety Applications

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Global Positioning System (GPS) is being increasingly used in active safety applications. One field of active safety in which navigation information can be used is Intersection Active Safety Applications (IASA) which requires a precise and continuous estimate of vehicle position and heading direction to function properly. In this paper an implementation of Extended Kalman Filter for estimation of vehicle position and heading direction in an intersection active safety application is presented. The algorithm was tested on a complex urban trajectory of 2 km long and showed very encouraging results.

Topics / Active Safety, Driver Assistance Systems, Intelligent Transportation Systems

1. INTRODUCTION

Today most of land navigation systems are based primarily on the GPS; however in an intersection active safety application (IASA), positioning requirements can not be satisfied by GPS alone due to possible occlusions by high buildings or heavy foliages and its poor precision and low position update frequency. Besides, in some intersection active safety applications such as vision based or radar based systems, precise vehicle heading direction is needed. Thus complementary onboard sensors should be implemented in the navigation system to achieve the required precision. In this paper an implementation of Extended Kalman Filter (EKF) [3] is presented.

The Extended Kalman Filter fuses data from GPS receiver and other complementary onboard sensors such as differential odometer, yaw rate sensor and longitudinal accelerometer to achieve the required performance for intersection active safety applications.

To verify the performance of the fusion algorithm a test was conducted in Alingsås, Sweden which showed encouraging results.

2. METHOD

The data used for testing the algorithm was collected by a test vehicle instrumented for active safety studies by Autoliv Development.

2.1 Sensors

The test vehicle was a standard Volvo V70, which was equipped with a GPS receiver (G12), a Cronos unit and a fiber optic gyro (FOG) which are further explained below.

GPS receiver collects position data (longitude, Latitude and Altitude) and Doppler derived speed and heading. The Cronos unit is a measurement device which offers direct connection of different components like the CAN bus and analog sensors in the vehicle. The Cronos out parameters which were used in the fusion algorithm are presented in Table 1. Fiber Optic Gyro is a high precision commercial fiber optic gyro.

Table 1 Fusion algorithm inputs

Measurements	Source	Sampling Frequency
Longitude	GPS	10Hz
Latitude		10Hz
Altitude		10Hz
Ground Speed		10Hz
Heading		10Hz
HDOP		10Hz
ABS Speed	Cronos	50Hz
Longitudinal Acceleration		50Hz
Yaw Rate		50Hz
Yaw Rate	FOG	50Hz

2.2 Extended Kalman Filter

Extended Kalman Filter (EKF) is an effective and versatile procedure for combining noisy sensor outputs to estimate the state of a system with uncertain dynamics. For the purpose of this paper the noisy sensors include GPS receiver, inertial sensors (accelerometer and gyroscope) and wheel speed sensor. The system state includes position, velocity, acceleration, heading (yaw) and heading rate. Uncertain dynamics includes unpredictable disturbance of the vehicle, whether caused by a human operator or by medium (e.g., wind or turn in the road). General formulation of an EKF is

$$\frac{d}{dt}x = f(x,t) + w(t) \qquad (1)$$

$$z = h(x) + v(t) \qquad (2)$$

where x is the state vector with the initial estimate of

$$\hat{x}_0 = E\langle x_0 \rangle \qquad (3)$$

and f, z and h are the dynamic model function, measurement vector and measurement model function respectively. The plant noise, $w(t)$, and measurement noise, $v(t)$, are assumed to be zero mean white noises.

Prediction step of an EKF can be described as

$$\hat{x}_k(-) = \hat{x}_{k-1}(+) + \int_{t_{k-1}}^{t_k} f(\hat{x},t)\cdot dt \qquad (4)$$

$$P_k(-) = \Phi_k P_{k-1}(+)\Phi_k^T + Q_{k-1} \qquad (5)$$

$$\Phi_k = e^{F_k\cdot(t_k - t_{k-1})}, F_k = \frac{\partial f}{\partial x}|_{x=\hat{x}_k} \qquad (6)$$

where Q is the dynamic disturbance covariance matrix and P is the error covariance matrix with the initial value of

$$P_0 = E\langle \tilde{x}_0 \tilde{x}_0 \rangle \qquad (7)$$

in which $\tilde{x}_0$ is the error of initial estimation of x. Correction step of an EKF can be presented as

$$\overline{K}_k = P_k(-)H_k^T(H_k P_k(-)H_k^T + R_k)^{-1} \qquad (8)$$

$$H_k = \frac{\partial h}{\partial x}|_{x=\hat{x}_K} \qquad (9)$$

$$\hat{x}_k(+) = \hat{x}_k(-) + \overline{K}_k\left[z_k - H_k\hat{x}_k(-)\right] \qquad (10)$$

$$P_k(+) = P_k(-) - \overline{K}_k H_k P_k(-) \qquad (11)$$

where K is the Kalman gain and R is the sensor noise covariance matrix.

In the problem addressed in this paper, the state vector, x, is

$$x = \begin{bmatrix}\theta & \phi & h & \psi & V & A & \dot{Y}\end{bmatrix}^T \qquad (12)$$

where θ is longitude, ϕ is latitude, h is altitude, ψ is heading direction, V is velocity, A is acceleration and $\dot{Y}$ is vehicle body yaw rate. The dynamic model function, f, in the addressed problem is

$$f = \begin{bmatrix}\frac{V_E}{\cos(\phi)(r_T + h)} & \frac{V_N}{(r_M + h)} & 0 & \dot{Y} & A & 0 & 0\end{bmatrix}^T \qquad (13)$$

where r_T is the transverse radius of curvature, r_M is the meridional radius of curvature and V_E, V_N are the east and north coordinates of velocity, respectively.

Presented sensor fusion algorithm uses three sources of measurement; GPS, Crornos and FOG (see Table 1) which have different and non-synchronized sampling frequency. Therefore in the measurement (correction) step of the Kalman filter (Equations 8-11), each source was measured and treated separately. In other words the measurement vector, z, measurement model function, h, measurement sensitivity matrix, H, and sensor noise covariance matrix, R, were different for each source of measurement as presented in the following equations:

$$z_{GPS} = \begin{bmatrix}\theta_{GPS} & \phi_{GPS} & h_{GPS} & \psi_{GPS} & V_{GPS}\end{bmatrix}^T \qquad (14)$$

$$h_{GPS}(x) = \begin{bmatrix}\theta & \phi & h & \psi & V\end{bmatrix}^T \qquad (15)$$

$$H_{GPS} = \frac{\partial h_{GPS}}{\partial x} = [I_{5\times5}\ 0_{5\times2}] \qquad (16)$$

$$R_{GPS} = diag(\sigma^2_{\theta_{GPS}} \quad \sigma^2_{\phi_{GPS}} \quad \sigma^2_{h_{GPS}} \quad \sigma^2_{\psi_{GPS}} \quad \sigma^2_{V_{GPS}}) \qquad (17)$$

where subscript GPS stands for the GPS data and σ_{Z_i} is uncertainty on measurement z_i.

$$z_{CNS} = \begin{bmatrix}V_{CNS} & A_{CNS} & \dot{Y}_{CNS}\end{bmatrix}^T \qquad (18)$$

$$h_{CNS}(x) = \begin{bmatrix}V & A & \dot{Y}\end{bmatrix}^T \qquad (19)$$

$$H_{CNS} = \frac{\partial h_{CNS}}{\partial x} = \begin{bmatrix}0_{3\times4}\ I_{3\times3}\end{bmatrix} \qquad (20)$$

$$R_{CNS} = diag(\sigma^2_{V_{CNS}}\ \sigma^2_{A_{CNS}}\ \sigma^2_{\dot{Y}_{CNS}}) \qquad (21)$$

where subscript CNS stands for the Cronos data.

$$z_{FOG} = \begin{bmatrix}\dot{Y}_{FOG}\end{bmatrix} \qquad (22)$$

$$h_{FOG}(x) = \begin{bmatrix}\dot{Y}\end{bmatrix} \qquad (23)$$

$$H_{FOG} = \frac{\partial h_{FOG}}{\partial x} = \begin{bmatrix}0 & 0 & 0 & 0 & 0 & 0 & 1\end{bmatrix} \qquad (24)$$

$$R_{FOG} = \begin{bmatrix}\sigma^2_{\dot{Y}_{FOG}}\end{bmatrix} \qquad (25)$$

where subscript FOG stands for the FOG data.

Equations 1-25 described the established EKF. For more details regarding the sensor fusion algorithm refer to [1].

3. RESULTS

In order to evaluate the developed fusion algorithm, it was tested on a complex urban roadway. Fig. 1 shows the test trajectory which included narrow streets, 7 meters width, where triple floor buildings restricted view of the sky and created urban canyon conditions.

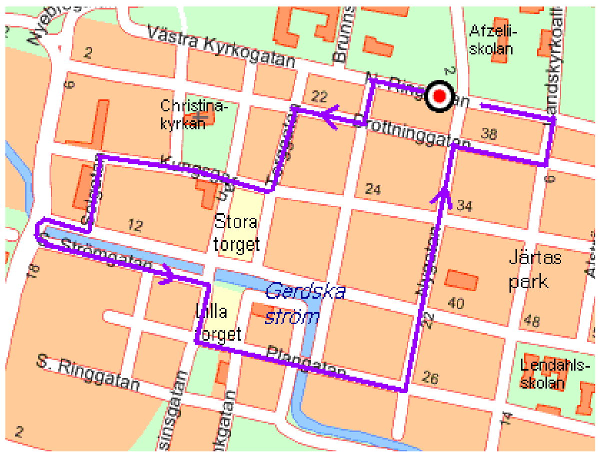

Fig. 1 Test trajectory

Unaided GPS position and associated uncertainty in GPS-alone position are presented in Fig. 2. As it can be seen GPS derived position is not available in some segments of trajectory due to signal blockage by high buildings, and even in most of the segments with GPS coverage, position measurement is too uncertain to be used in an IASA.

The estimated trajectory by EKF is presented in Fig. 3. As it can be seen goals of filling the gaps of GPS coverage and giving a smooth and continuous position are achieved.

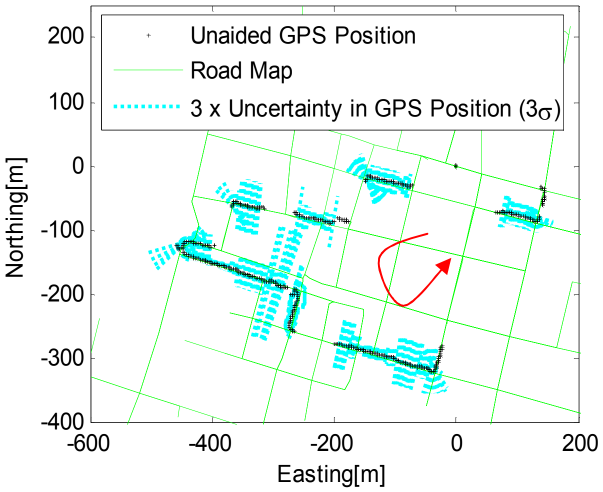

Fig. 2 Unaided GPS trajectory and associated uncertainty in position

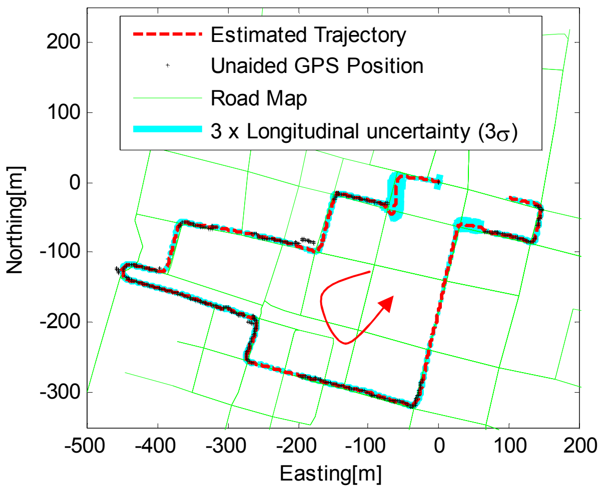

Fig. 3 Longitudinal uncertainty (3 σ), plotted perpendicular to the vehicle trajectory

Kalman filter maintains two types of variables: estimated state vector and covariance matrix. Covariance matrix is a measure of estimation uncertainty. Estimation uncertainty in position both in longitudinal (tangent to vehicle trajectory) and lateral direction (perpendicular to vehicle trajectory) is presented in Fig. 3 and Fig. 4. During GPS blockage periods uncertainty in both directions increases. Uncertainty increase in longitudinal direction is mostly due to integration of speed uncertainty during this time, while lateral uncertainty increase is primarily due to uncertainty in heading which can cause large lateral position uncertainty in long distances. It can also be observed that lateral uncertainty changes to longitudinal uncertainty as the vehicle turns in an intersection. It can be concluded that accurate estimation of speed and heading is crucial for proper functioning of the fusion algorithm. In Fig. 5 estimation uncertainty in lateral and longitudinal directions are overlaid for better comparison.

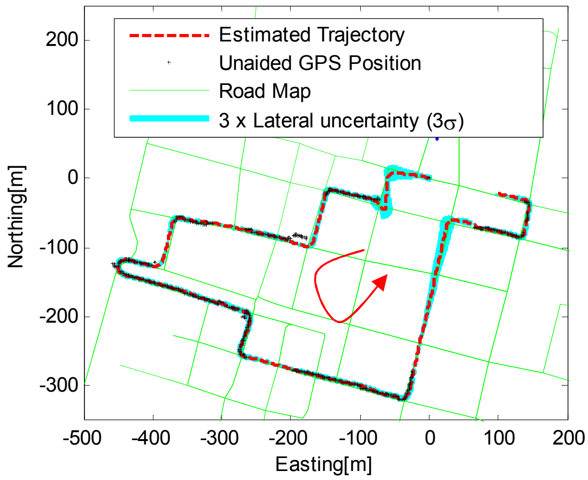

Fig. 4 Lateral uncertainty (3 σ), plotted perpendicular to the vehicle trajectory.

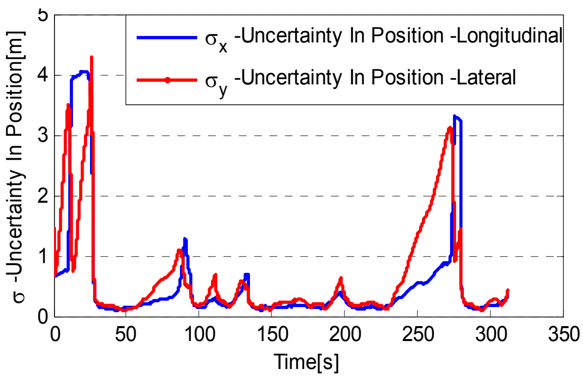

Fig. 5 Lateral and longitudinal uncertainties

As mentioned in introduction, precise estimation of heading direction is a requirement for an intersection active safety application. Although a high precision commercial fiber optic gyro was used in the test vehicle, still yaw rate needed to be fused with other measurements for compensation of errors caused by integration of noisy yaw rate measurement. In addition absolute heading direction was needed as an initial value for integration of yaw rate.

Fig. 6 shows estimated heading direction by EKF, GPS Doppler derived heading direction and integrated yaw rate collected from fiber optic gyro. As it can be seen the EKF succeeded in filtering the noisy GPS Doppler derived heading direction based on the yaw rate measurements.

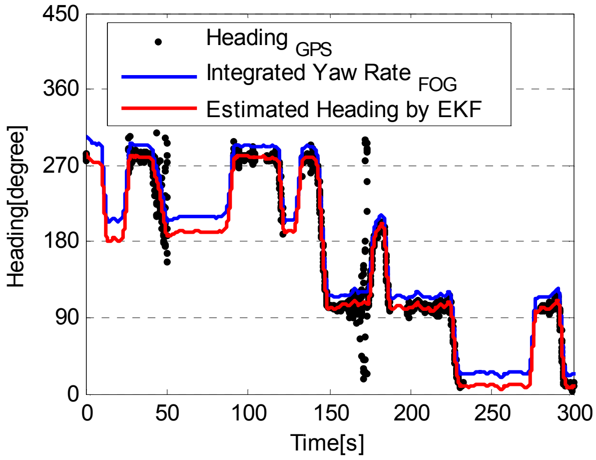

Fig. 6 Heading measurements and estimated heading

For better presentation of heading direction estimation by established EKF, "difference between Doppler derived heading and integrated yaw rate" and "difference between estimated heading and integrated yaw rate" are given in Fig. 7. It can be observed that difference between estimated heading direction and integrated yaw rate is not constant and is affected by GPS heading direction and other fused measurements.

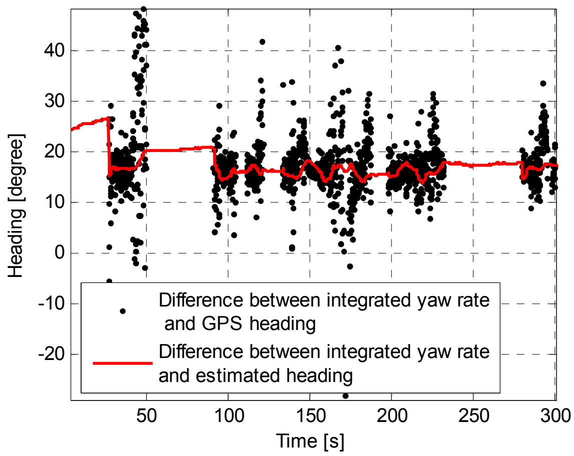

Fig. 7 "Difference between integrated yaw rate and Doppler drived heading" and "Difference between integrated yaw rate and estimated heading"

Fig. 8 shows heading estimation uncertainty which goes below 1 degree after first 40 seconds and increases slightly during GPS blockage.

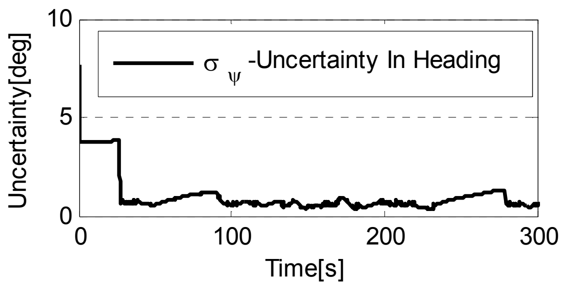

Fig. 8 Heading estimation uncertainty

4. CONCLUSION

A sensor fusion algorithm for vehicle positioning in intersection active safety applications, based on Kalman filtering is presented. The developed extended Kalman filter integrates complementary onboard sensors and GPS data to achieve continuous and precise position and heading direction of the vehicle.

The system was tested on a complex urban roadway where GPS signal occlusion was observed frequently. The GPS was available in only about 70% of the total trajectory length. The integrated positioning system provided very encouraging results.

Heading estimate became more precise by fusion of Doppler derived heading and yaw rate from Fiber Optic Gyro. Heading estimation uncertainty was about 1 degree. The yaw rate sensors used in this paper were expensive non-automotive grade equipment; however considering the sensor developments, these results can be obtained by automotive grade sensors in near future.

Position estimation uncertainty both in longitudinal (tangent to vehicle trajectory) and lateral direction, during GPS coverage, was 0.3 m in average. The increase in longitudinal uncertainty is about 0.5m for each 100m of GPS blockage, and this value for lateral uncertainty is about 1.5m for each 100m of GPS blockage.

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