TECHNISCHE UNIVERSITÄT DRESDEN

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EPE AND SPEED ADAPTIVE EXTENDED KALMAN FILTER FOR VEHICLE POSITION AND ATTITUDE ESTIMATION WITH LOW COST GNSS AND IMU SENSORS

INTRODUCTION

This poster presents a novel approach for an adaptive Extended Kalman Filter (EKF), which is able to handle bad signal quality caused by shading or loss of Doppler Effect for low cost Global Navigation Satellite System (GNSS) receiver and Inertial Measurement Unit (IMU) sensors, fused in a loosely coupled way. It uses the estimated position error (EPE) from the GNSS device, as well as velocity, to calculate the standard deviation for the measurement uncertainty matrix of the Kalman Filter. It estimates the position of a vehicle and its attitude (roll, pitch), as shown in Fig. 1.

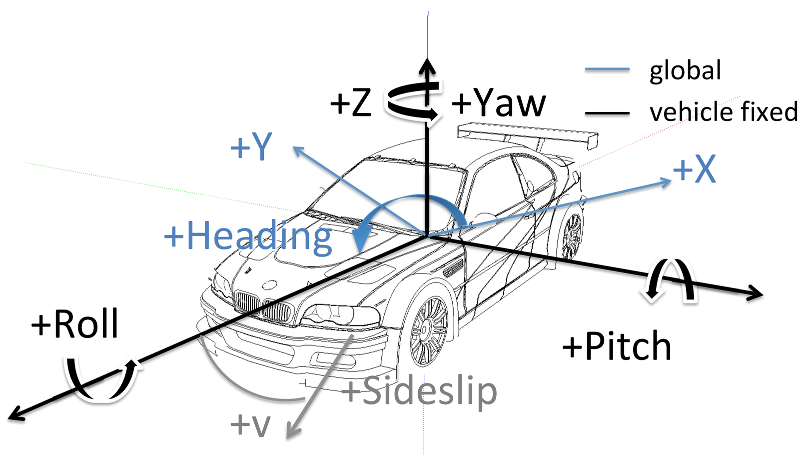

Fig. 1: Vehicle with coordinate system

ADAPTIVE EXTENDED KALMAN FILTER

The state transition function is defined by

$$\mathrm{x}_{\mathrm{k}+1} = \begin{bmatrix} \mathrm{x} + \frac{\mathrm{v}}{\dot\psi}\left(-\sin(\psi) + \sin\left(\mathrm{T}\dot\psi + \psi\right)\right) \\ \mathrm{y} + \frac{\mathrm{v}}{\dot\psi}\left(\cos(\psi) - \cos\left(\mathrm{T}\dot\psi + \psi\right)\right) \\ \mathrm{v} + \mathrm{Ta}_{\mathrm{x}} \\ \psi + \mathrm{T}\dot\psi \\ \phi + \mathrm{T}\dot\phi \\ \Theta + \mathrm{T}\dot\Theta \end{bmatrix} \qquad (1)$$

The positions x and y, the speed and heading are measured with a low cost GNSS receiver. The attitude is calculated with an orientation filter (presented in (Madgwick, 2010) and improved by this work).

The novel approach, presented in this work, is easy to implement and quickly calculates adaptive standard deviations for the measurement noise covariance matrix R.

$$\mathrm{R} = \mathrm{diag}\left[\sigma_{\mathrm{x}}^2\ \sigma_{\mathrm{y}}^2\ \sigma_{\mathrm{v}}^2\ \sigma_{\psi}^2\ \sigma_{\phi}^2\ \sigma_{\Theta}^2\right] \qquad (2)$$

Position Measurement Uncertainties

In every EKF filterstep, the standard deviations for σ_{x} and σ_{y} are calculated in relation to the speed and the estimated position error (EPE) that is provided by the GNSS module itself.

$$\sigma_{\mathrm{x}}^2 = \sigma_{\mathrm{y}}^2 = \mathrm{c} \cdot \sigma_{\mathrm{v}}^2 + \sigma_{\mathrm{EPE}}^2 \qquad (3)$$

with

$$\sigma_{\mathrm{v}} = (\mathrm{v} + \epsilon)^{-\xi} \qquad (4)$$

$$\sigma_{\mathrm{EPE}} = \zeta \cdot \mathrm{EPE} \qquad (5)$$

Resulting shape of σ_{x}^2 and σ_{y}^2 as f(v, EPE) is shown in Fig. 2

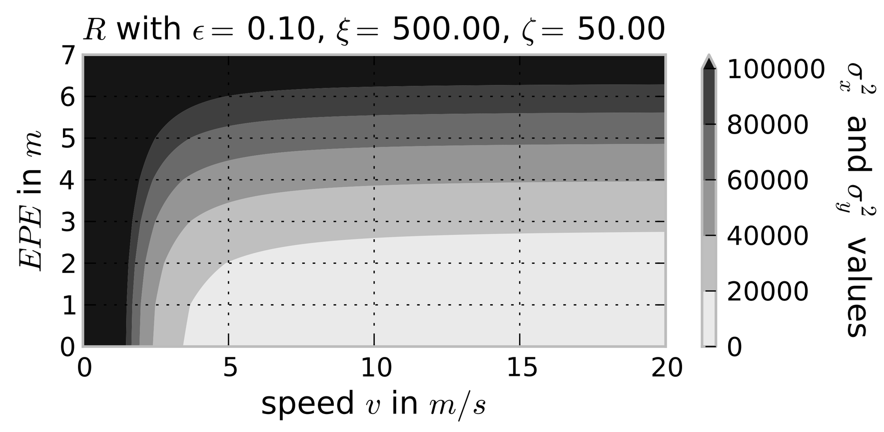

Fig. 2: Adaptive σ_{x}^2 and σ_{y}^2 as f(v, EPE)

Attitude Measurement Uncertainties

The uncertainties for roll and pitch are adaptively calculated, as suggested by (Madgwick, 2010), depending on the vehicle accelerations in the appropriate directions.

$$\sigma_{\Theta} = \left(\rho + \gamma \cdot \mathrm{a}_{\mathrm{y}}\right)^2 \qquad (6)$$

$$\sigma_{\psi} = \left(\rho + \gamma \cdot \mathrm{a}_{\mathrm{x}}\right)^2 \qquad (7)$$

To evaluate the proposed filter, multiple simulations and real world measurements were conducted.

SIMULATION

To evaluate the adaptive EKF, a typical urban scenario, with shading from a building, as well as a vehicle stop and cornering, was simulated (see Fig. 3).

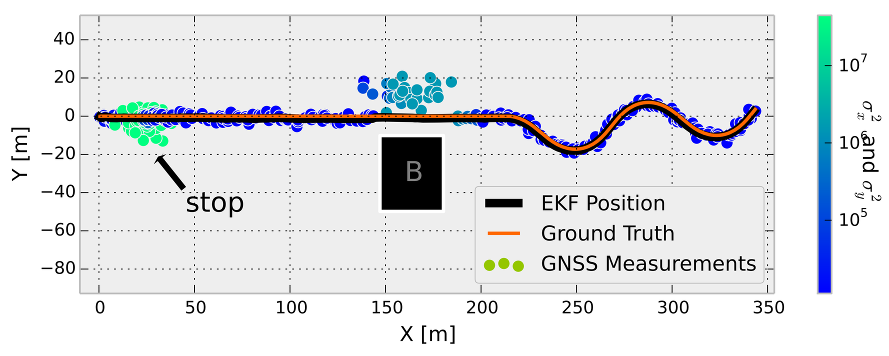

Fig. 3: Simulated urban scenario data

The cross track error is introduced to quantify the filter performance with respect to ground truth (GT) trajectory.

$$\mathrm{CTE}_{\mathrm{x}} = \mathrm{x}_{\mathrm{GT}} - \mathrm{x} \qquad (8)$$

To compare the estimated trajectory with a non-adaptive EKF, the position estimation was performed with several datasets for GNSS position measurements, generated by random Gaussian noise around the ground truth position. The resulting cross track errors (CTE) are shown in Fig. 4.

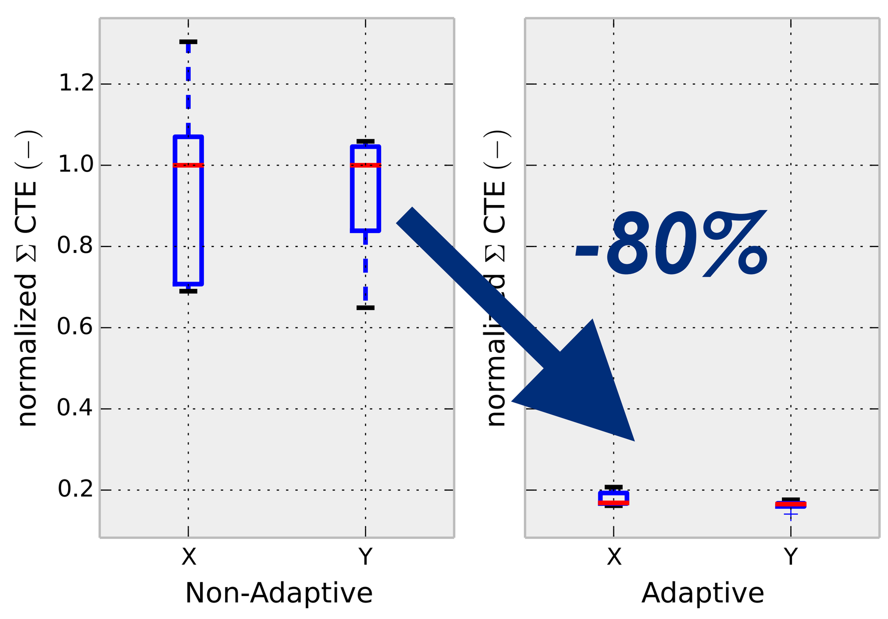

Fig. 4: Cross-track-error of standard and adaptive EKF: 80% reduction.

EXPERIMENTAL EVALUATION

Equipment

The ground truth was determined with a multi-frequency aerial antenna (Javad GrAnt-G3T) and receiver (Javad Delta), corrected by a virtual reference station (VRS) and Satellite Positioning Service of the German State Survey (SAPOS) data via a GPRS modem (come2ascos GenPro).

The measurement and control data of the filter were logged by a LSM303 3-axis accelerometer and 3-axis magnetometer, ITG-3200 3-axis gyro and PA6H GNSS receiver. The sensors are available with the Tinkerforge IMU Brick and GPS Bricklet.

Results

Fig. 5 shows the trajectory of the adaptive EKF and the ground truth.

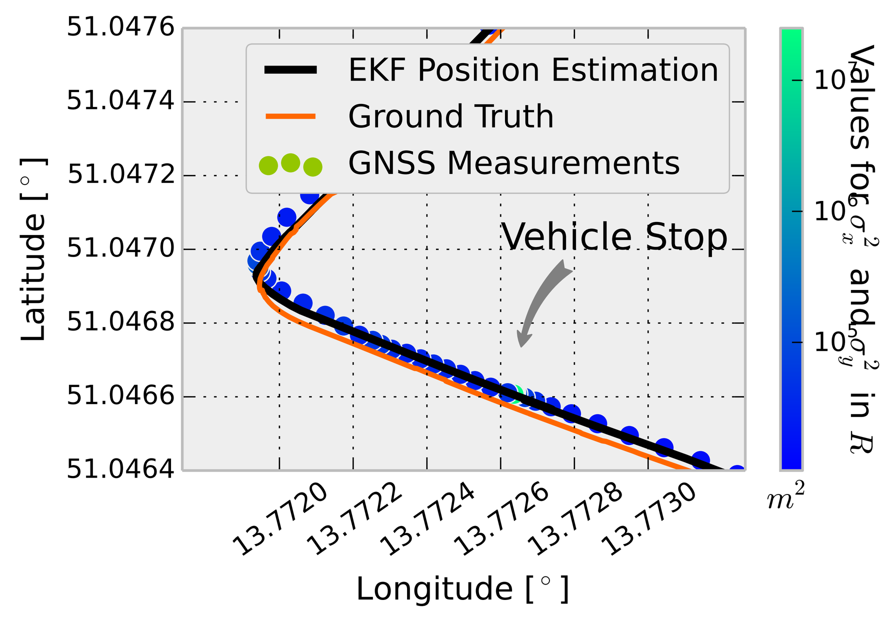

Fig. 5: Part of a test drive with adaptive values of measurement uncertainty values for matrix R

CONCLUSION

The filter improves the position estimation under partly bad signal quality. In addition to that, the filter also performs pretty well in dynamic situations and does not lose the ability to follow dynamic vehicle movements.

IMPLEMENTATION EXAMPLE

A Python implementation, the data and all figures are available at: http://balzer82.github.io/ICINCO-2014

REFERENCES

Madgwick, S. (2010). An efficient orientation filter for inertial and inertial/magnetic sensor arrays. Report x-io and University of Bristol.

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