IMPROVED LOCALISATION FOR TRAFFIC FLOW CONTROL

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Abstract

Localisation of vehicles plays an important role in future traffic control concepts. To solve this task several sensors may be used. Each of these different sensors has its own, specific disturbances. Incremental measurement of wheel rotation to get information about the covered distance is distorted by slip and rugged roads, measuring the orientation of the vehicle by means of a magnetometer suffers from internal and external disturbing magnetic fields, and vehicle vibrations disturb yaw rate measurement.

A method to improve autonomous localisation based on Kalman filtering is presented. By estimating the variance of the different sensor data the Kalman Filter parameters can be varied to achieve improved system behaviour. Results are presented for an in-town drive. The system is just about to be implemented in real-time in a test vehicle at the University of Karlsruhe.

Keywords: data-fusion, Kalman filter, autonomous localisation.

1. Introduction

Rising traffic creates the need for intelligent methods of traffic control. A basic requirement for intelligent control of traffic flow is the ability of a vehicle to navigate for a limited period of time without external aid. Thus the need for a method to estimate its position in respect to a known origin is obvious.

If possible, a localisation system should make use of sensors that can already be found in a modern vehicle to keep the costs and the complexity of the overall system low. In the system which is to be presented, the incremental sensors at the wheels which are used by the anti-lock braking system are chosen as basic sensors. To improve the quality of the localisation system, a magnetic field probe is applied as sensor for the terrestrial magnetic field. Additionally, data from a yaw rate sensor are available.

Yaw rate sensors will be used not only by the navigation system, but also by future improved driving stability control systems.

Each of the sensors has its own specific disturbances. v.d. HARDT, (1992) showed that Kalman filtering is a suitable method for fusing data provided by the different sensors. Modelling the sensor errors in combination with a Kalman filter approach improves the system performance significantly compared to the simple use of each sensor information alone.

2. Position Determination

The position of a vehicle in respect to a known origin O is definitely determined by the vehicle's x- and y-co-ordinates and its orientation Θ (*Fig. 1.*)

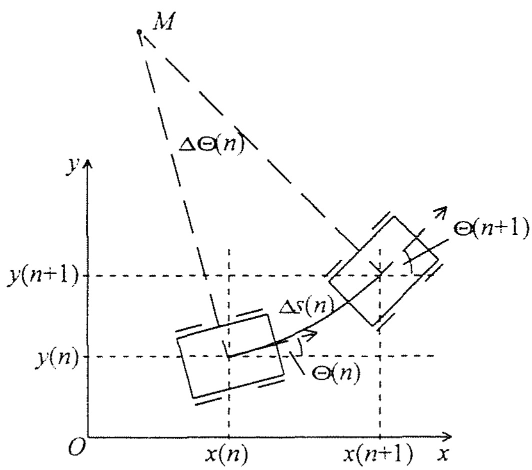

Fig. 1. Position of a vehicle

If the position of a vehicle is to be determined at time $t_n = t_0 + nT$, it is the task of a localisation system to determine the position at time $t_{n+1}[x(n+1), y(n+1), \Theta(n+1)]$ based on the (known) position at time $t_n[x(n), y(n), \Theta(n)]$ using the sensor data and applicable data-fusion methods.

2.1 Assumptions and Approximations

To calculate the position $\underline{x}(n) = [x(n), y(n), \Theta(n)]$ of the vehicle it is assumed, that during each localisation cycle T the vehicle moves with a constant speed on a circle with a constant diameter. Centre of this circle is the instantaneous pole M (*Fig. 1*). If the localisation cycle T is sufficiently short, this assumption can be considered fulfilled.

To determine the new position from the covered distance $\Delta s(n)$ and the angular orientation increment $\Delta\Theta(n)$ during one localisation cycle, the arc $\Delta s(n)$ is approximated by the straight line $\Delta h(n)$ (*Fig. 2*). This approximation is based on the assumption that the angular increment $\Delta\Theta$ is not too big. The approximation error is 1.1% for an angular increment of 30° . Under normal conditions the angular increment is much smaller, so the approximation error is acceptably small.

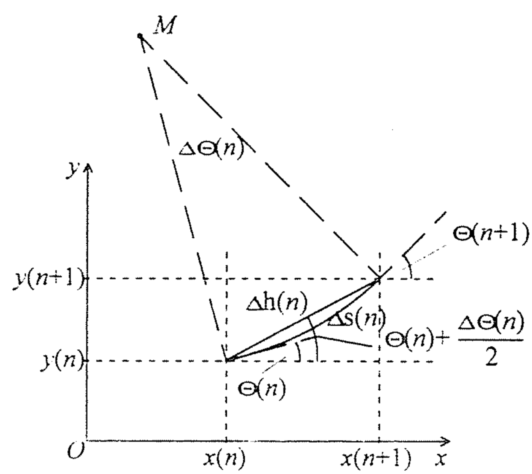

Fig. 2. Approximation of $\Delta s(n)$

2.2 Determination of the Vehicle's Position

Under the assumption and approximations made above, the following three recursive equations for determination of the position can be found:

$$x(n+1) = x(n) + \Delta s(n) \cdot \cos\left(\Theta(n) + \frac{\Delta\Theta(n)}{2}\right), \tag{1a}$$

$$y(n+1) = y(n) + \Delta s(n) \cdot \sin\left(\Theta(n) + \frac{\Delta\Theta(n)}{2}\right), \tag{1b}$$

$$\Theta(n+1) = \Theta(n) + \Delta\Theta(n). \tag{1c}$$

The angular increment $\Delta\Theta(n)$ as well as the orientation $\Theta(n)$ appear in every equation, in *Eq.* (1a) and (1b), which determine the new x- and y-co-ordinates, non linearly connected with the covered distance $\Delta s(n)$. Thus it is especially important to determine the orientation of the vehicle and the angular increment as exactly as possible.

Under the condition of exactly known geometric properties of the wheels and the axle, it is possible to determine the covered distance of the vehicle $\Delta s(n)$ as well as the angular increment $\Delta\Theta(n)$ solely from the distances covered by two wheels of a single axle:

$$\Delta s(n) = \frac{\Delta s_r + \Delta s_l}{2}, \tag{2a}$$

$$\Delta\Theta(n) = \frac{\Delta s_r - \Delta s_l}{L}. \tag{2b}$$

Δs_r and Δs_l are the distances covered by the right respectively left wheel during the localisation period, L is the effective tread.

The covered distance is readily determined by this method, while the determination of the orientation, i.e. the angular increment, is not sufficiently possible. Especially the integration process in *Eq.* (1c) augments errors due to the use of incremental information only. The reasons for this are explained in chapter 3.2.1.

The final localisation system uses the average of the covered wheel distances to determine the covered distance of the vehicle, while the orientation of the vehicle is determined using data fusion methods explained in chapter 4 for the data of all sensors that provide information on the angular increment and/or the orientation.

3. Used Sensing Devices

Sensors used for localisation tasks can be divided in two classes. Proprioceptive sensors provide differential information on physical quantities, i.e. a value is measured in relation to the vehicle's position after the last localisation cycle. Proprioceptive sensors are incremental shaft encoders, accelerometers or yaw rate sensors. Exteroceptive sensors measure a physical quantity, e.g. the orientation of a vehicle, absolutely in relation to an external reference. Examples are a compass, triangulation methods or cameras mounted on the vehicle.

In the system which is dealt with here, two different kinds of proprioceptive sensors are used. Besides the incremental encoders of the anti-lock braking system a yaw rate sensor is mounted between the front seats. A compass of Förster type is used to measure the terrestrial magnetic field and is the only exteroceptive sensor for the vehicle's orientation.

3.1 Description of the Sensors

Measurement of the wheel speed is performed by inductive sensors which scan the teeth of a toothed wheel mounted on the axle of every wheel. The signals are conditioned using differential amplifiers and Schmitt triggers and then connected to counter ports of a microcontroller. The microcontroller latches the actual counter value for the first and last slope of the signal for each wheel during a localisation cycle as well as the number of slopes actually encountered for each wheel. The covered distance may be determined as:

$$\Delta s = 2 \cdot \pi \cdot R \cdot \frac{T \cdot f_C}{Z} \cdot \frac{(N_{Sl} - 1)}{(N_l - N_f)}. \tag{3}$$

Here, R is the radius of each wheel, N_{Sl} the number of slopes, Z the number of teeth on the toothed wheel, T the localisation cycle, f_C the frequency of the counter and N_f and N_l the counter values for the first and last slope. As the amplitude of the sensor signals decreases with decreasing speed, the suitability of the wheel sensors is limited to speeds above 5 km/h.

To measure the yaw rate, which is the rotational speed of the vehicle chassis in regard to the vertical axis, a vibratory gyroscope (MURATA, 1990) is applied. The measurement effect is based on the measurement of Coriolis force that detunes a vibrating, triangular bar.

The magnetic field probe is a Förster sensor that consists of two coils which are arranged with an angle of 90° to each other. They are coiled around a cross-shaped ferro-magnetic former. So it is possible to measure the projection of the terrestrial magnetic field into the horizontal plane. A ramp-shaped current drives the coils from negative saturation to positive saturation, the saturation region is measured by a superimposed, high-frequency AC-current. Superimposed magnetic fields yield in a shifting of the saturation region, which serves to measure the superimposed magnetic field.

3.2 Errors of the Proprioceptive Sensors

3.2.1 Incremental Wheel Sensors

The use of wheel sensors to measure the covered distance and the angular increment of the orientation is corrupted by systematic and stochastic errors. Systematic errors arise mainly from geometric inaccuracies. The wheel diameters vary with the vehicle speed, the tire pressure, temperature and the vehicle load. The effective tread L (*Eq.* (2b)) varies mainly with the speed and the curve radius. This effect is especially big for the front wheels, because here the effective tread depends, caused by the mechanical construction, strongly from the angle of turn and the wheel suspension. Stochastic errors are caused by variable slip, road inclination, rough road etc. Partly, the systematic errors can be minimized by calibration runs, but the stochastic errors can hardly be detected. Because of this, the measurement errors of the angular increment $\Delta\Theta$ using wheel sensors are modelled as being a constant which is used for the Kalman calculations. Additionally, plausibility checks help to avoid mistakes during anti-lock braking or during situations with extremely big slip. At speeds below about 10 kilometres per hour, the angular information from the wheel sensors is ignored due to the sensor problems at low speed (cf. section 3.1).

3.2.2 Vibratory Gyroscope

The gyroscope suffers from two different errors. First, there has to be considered an offset drift, which is varying slowly with the temperature. This drift is compensated using a long-term highpass filter. The second error source are higher frequency disturbances which are mainly caused by vibrations of the vehicle chassis. To get a measure for these errors, the signal from the gyroscope is oversampled and a second-order polynomial is interpolated using the standard least-squares algorithm. The interpolation error is used to determine the variance $\sigma^2_{\Delta\Theta,GS}$ of the yaw rate error. As the variance is non-zero even when the interpolation error disappears, the variance is determined as shown in *Fig. 3*. A minimum variance is chosen for a disappearing interpolation error, and for the highest observed error a maximum variance is chosen.

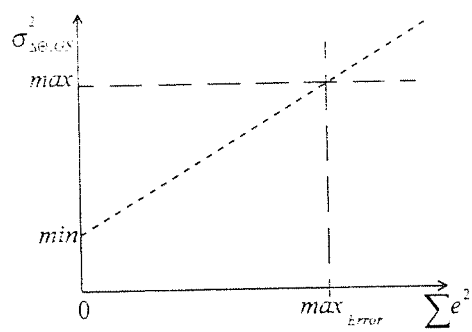

Fig. 3. Determination of yaw-rate error variance

3.3 Magnetic Field Probe

Error detection and error compensation for the magnetic field probe as the only exteroceptive sensor in the system requires special attention. The errors can be separated into static and dynamic errors as well as into orientation-dependent and orientation-independent errors.

3.3.1 Sources of Error

The main sources of error for the compass can be found in magnetic fields that are superposed to the terrestrian field. Internal interference fields are those fields that have their origin from within the vehicle. They can be subdivided into orientation-dependent and -independent fields. Orientation-independent fields arise from permanent magnetic parts of the vehicle chassis or from on-board DC loops caused by consumers like a rear window defroster. They yield a shifting of the origin for the compass. Orientation-dependent interference fields are caused by poles induced in magnetically soft parts of the chassis and effect a distortion of the circle expected for the compass when turning the vehicle to an elliptical curve. Together the static fields result in a situation as shown in *Fig. 4*. As long as there are no changes made in the chassis (turning consumers on and off are such changes!) the above described static fields interfere with the terrestrial magnetic field and can be measured and compensated by calibration runs.

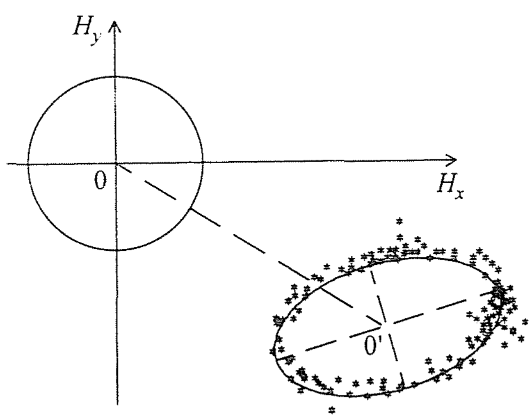

Fig. 4. Shifting and distortion of the magnetic field probe signal

Additionally, dynamic fields are interfered, caused either by the vehicle itself (consumers, sliding sun roofs) or interfered from the outside (tramway overhead contact lines, trucks that are overtaken). To detect and compensate errors caused by these fields it is assumed that the dynamic errors do not cause distortion but only shifting of the magnetic curve in *Fig. 4*. The errors caused by the vehicle itself can be minimised by a suited mounting position for the compass and by detection of on-board reasons like the rear win- dow defroster or the sliding roof and compensation by additive calibration drives. Besides of the errors caused by interfering fields errors arise from the sensor construc- tion itself. The magnetic field is measured in two horizontal directions only. Measuring the horizontal projection of the terrestrial magnetic field causes errors when the vehicle moves upward or downward, if the road is inclined or if the vehicle is asymmetrically loaded. These errors can not be detected with the used sensors.

3.3.2. Error Detection and Compensation

The compass generates 24 measurement values during every localisation cycle. During a calibration drive the parameters of the shifted ellipse are determined, so that the measured values can be re-transformed to the unit circle. Considering the mounting angle to the chassis length-axis and the magnetic declination, it is possible to determine the orientation of the vehicle straightforward.

For validation of the measured values a ring-shaped and a sector-shaped filter are used. After transformation to the unit circle the distance of the values to the origin is calculated. If the distance is significantly different from the expected, the values are considered invalid (ring-shaped filter). Equally, the deviation of the orientation values Θ_i is judged, and values with a deviation from the mean $\overline{\Theta}$ higher more than a predetermined angle α_{filter} are considered invalid. The valid measurement values (*Fig. 5*) are then used to determine the orientation Θ_{MFP} as mean of the valid values Θ_i.

The hardest problem to be dealt with when using the compass is the compensation of the ellipse shifting caused by dynamic disturbances. Here, all available values from the field probe are used. The shifting of the origin is performed, when the measured values cover a angular region sufficiently large, the number of measured values is high enough and if the calculated value for the shifting is constant for several localisation cycles. If these assumptions are true, then the shifting is performed by interpolating a unit circle using the sensor data and the shifting parameters are updated.

To determine the variance of the measurements of the magnetic field probe, the mean distance of the measured and re-transformed values to the unit circle is taken into account. The principle is the same as described

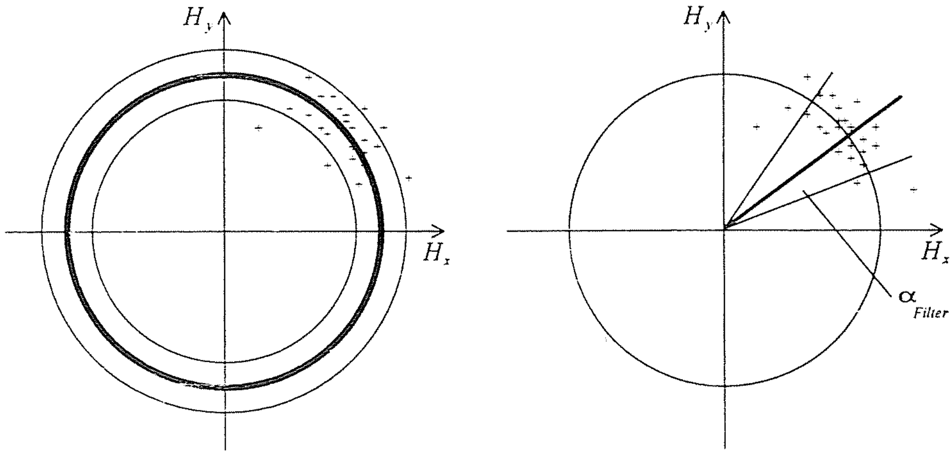

Fig. 5. Ring- and Sector-Shaped Filter for Validation of the Compass Values

for the yaw rate sensor (section 3.2.2). Test drives showed, that instead of a linear function between the two fixed points of *Fig. 3*, a square root function yields better results.

4. Determination of the Orientation using Kalman Filters

4.1. Signal Model to Determine the Orientation

To determine an optimal estimation for the orientation of the vehicle using the redun- dant information provided by the different sensors, the following signal model is used as a base for the filtering process:

$$\begin{bmatrix} \Delta\Theta(n+1) \\ \Theta(n+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \cdot \begin{bmatrix} \Delta\Theta(n) \\ \Theta(n) \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} \cdot u(n) \tag{4}$$

Θ, the signal vector, is composed of the two variables $\Delta\Theta$ and $\Theta \cdot u(n)$ is the (unknown) value of the angular acceleration at instant n. $u(n)$ is modelled as white noise with mean zero and variance σ_u^2. $\Delta\Theta(n)$ and $\Theta(n)$ the output variables of the system that are corrupted by noise depending on the used sensors:

$$\begin{bmatrix} \Delta\Theta_m(n) \\ \Theta_m(n) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \cdot \begin{bmatrix} \Delta\Theta(n) \\ \Theta(n) \end{bmatrix} + \begin{bmatrix} e_{\Delta\Theta}(n) \\ e_{\Theta}(n) \end{bmatrix} \tag{5}$$

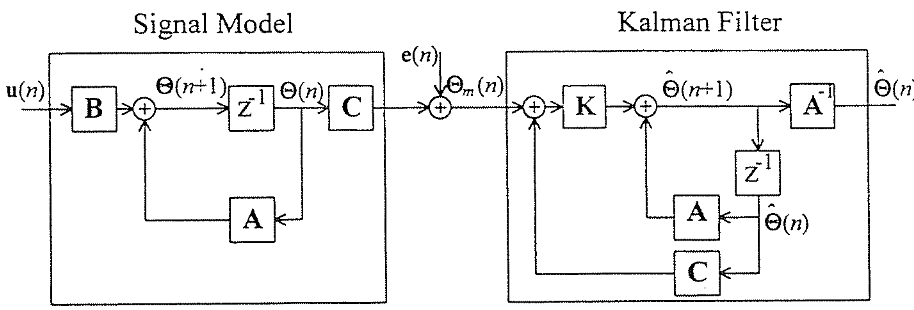

Fig. 6. Signal Model and Kalman Filter Structure

The output noise $e_{\Delta\Theta}(n)$ and $e_{\Theta}(n)$ is modelled as gaussian noise with mean zero that is statistically independent. The variance matrix $\mathbf{V}_e$ of the noise for the different sensor types is determined as described in chapter 3.

Fig. 6 shows the signal model and the Kalman filter structure. A prediction for one step is performed, which is then used to estimate the optimal values of $\Delta\Theta(n)$ and $\Theta(n)$ (KRONMÜLLER 1992, and KROSCHEL 1988).

4.2. Recursive Evaluation of the System

Using the matrices

$$\mathbf{A} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} , \quad \mathbf{b} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} , \quad \mathbf{C} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad \text{and} \quad \mathbf{K} = \begin{bmatrix} K_{11} & K_{12} \\ K_{21} & K_{22} \end{bmatrix} \tag{6}$$

for the evaluation of the system shown in *Fig. 6*, the estimated value for the orientation and angular increment at instant n is:

$$\hat{\Theta}(n+1) = (\mathbf{A} - \mathbf{K}(n) \cdot \hat{\Theta}(n) + \mathbf{K}(n) \cdot \Theta_m(n) \tag{7}$$

with the recursive equations

$$\mathbf{K}(n) = \mathbf{A}\mathbf{V}_k(n)\mathbf{C}^T[\mathbf{V}_e(n) + \mathbf{C}\mathbf{V}_K(n)\mathbf{C}^T]^{-1} \tag{8a}$$

$$\mathbf{V}_K(n+1) = (\mathbf{A} - \mathbf{K}(n)\mathbf{C})\mathbf{V}_K(n)(\mathbf{A} - \mathbf{K}(n)\mathbf{C})^T +$$

$$+\mathbf{K}(n)\mathbf{V}_e(n)\mathbf{K}^T(n) + \mathbf{B}\sigma_u^2\mathbf{B}^T \; . \tag{8b}$$

Here, $\mathbf{V}_K(n+1)$ is the covariance of the prediction and $\mathbf{K}(n)$ is the filter gain. The elements K_{ij} of the filter gain matrix are:

$$\begin{aligned}
K_{11}(n) &= V_{K,11} \cdot V_{K,22} - V_{K,12} \cdot V_{K,21} + V_{K,11} \cdot \sigma_\theta^2(n) \\
K_{12}(n) &= V_{K,12} \cdot \sigma_{\Delta\Theta}^2(n) \\
K_{21}(n) &= V_{K,11} \cdot V_{K,22} - V_{K,12} \cdot V_{K,21} + (V_{K,11} + V_{H,21}) \cdot \sigma_\theta^2(n) \\
K_{22}(n) &= V_{K,11} \cdot V_{K,22} - V_{K,12} \cdot V_{K,21} + (V_{K,12} + V_{H,22}) \cdot \sigma_{\Delta\theta}^2(n) \qquad (9)
\end{aligned}$$

$V_{K,ij}$ are the elements of the prediction covariance matrix $\mathbf{V}_K(n)$, $\sigma_\Theta^2(n)$ the variance of the noise of the orientation measurement and $\sigma_{\Delta\Theta}^2(n)$ the variance of the angular increment noise.

4.3. Cascading of the Kalman Filters

Using all three sensors that provide information on the orientation or the angular increment a Kalman filter structure is shown in *Fig. 7.* The first Kalman filter (KF1) fuses the information from the magnetic field probe and the gyroscope to obtain an improved estimate for the vehicle's orientation. The following, second Kalman filter (KF2) uses the information provided by the wheel sensors. The value for Θ_m at the input of KF2 is the output of KF1. The corresponding variance for the orientation measurement is $V_{K,22}$, the prediction variance of KF1.

In case of a sensor defect, for a first step the information provided by that sensor is kept from the prior period and the sensor variance is increased. If the sensor defect lasts for several localisation periods, the structure of the cascaded Kalman filters is changed. If the missing information is either the one from the gyroscope or the one from the wheel sensors, the system keeps operating with a single Kalman filter as described in section 4.2. If the defect sensor is the compass, the Kalman filter structure has to be changed. The absolute value for the orientation cannot be measured, so the absolute orientation is estimated by adding one of the incremental sensor values to the optimal value estimated one step in the past (*Fig. 8*).

Here, each of the input values for the Kalman filter algorithm is given a variance as determined for the incremental sensors.

5. Experimental Results

In the following section some of the experimental results are presented. First, values for the estimated variance limits that led to a satisfactory

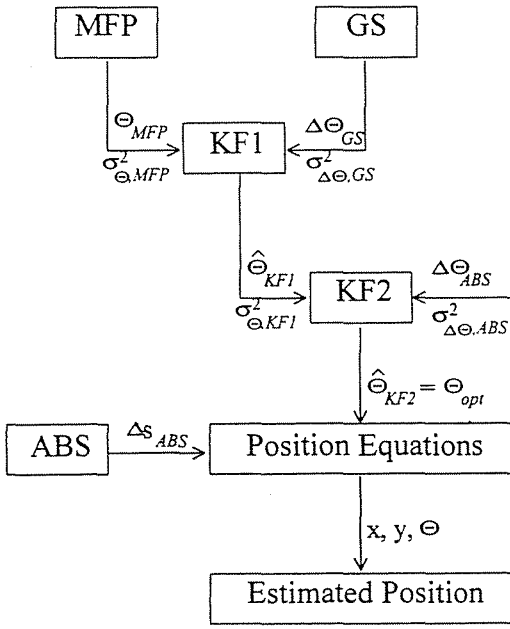

Fig. 7. Signal Flow for Data Fusion

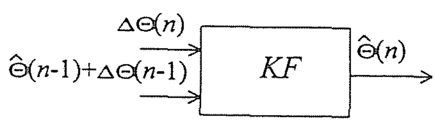

Fig. 8. Reduced Kalman filter structure with compass defect

system behaviour are presented. Thereafter, the new algorithm is compared to the simple combination of the sensor values for different test drives.

5.1. *Choosing the Variance and Algorithm Parameters*

The geometrical properties of the test vehicle were determined during several calibration drives. These include straight drives to determine the wheel diameters under dynamic circumstances as well as several cycling drives to determine the tread.

During the development and test it showed, that the sensor variance region is the most important tool to tune the algorithm. For the wheel sensors, a constant variance $\sigma^2_{\Delta\Theta,ABS}$ of (0.5° per system cycle)^2 was chosen. In general, yaw rate measurement results in a better reliability of the data, so the minimum value $\sigma^2_{\Delta\Theta,GS}$ for the gyroscope (cf. *Fig. 3*) was chosen to be (1° per system cycle)^2 and the maximum value is (2° per system cycle)^2 for the maximum interpolation error observed during test drives.

When choosing the variance estimation for the magnetic field probe, it showed that a relatively high variance even for undisturbed measurements improves system behaviour. The reason is that the compass as the only exteroceptive sensor has a high long-term influence on the orientation estimation. Dynamic disturbances, which last for only a few system cycles, can easily be suppressed by choosing the compass minimum variance of $(10°)^2$. Here, the maximum variance was chosen as $(50°)^2$.

The variance of the unknown system input noise, the angular acceleration, was chosen to be fixed as (10° per (system cycle)^2)^2. For further investigations, a functional link between the vehicle speed and the system input variance might provide even better results.

5.2 In-Town Test Drive

The test drive presented here is a track in Karlsruhe. *Fig. 9* shows the results for the Kalman filter algorithm compared to algorithms that use only the compass data or only the gyroscope data for determination of the vehicle's orientation. Starting point is at the coordinate origin in the lower right corner of *Fig. 9*. The black asterixes are reference points taken from a map, after every 100 localisation cycles a cross is printed on the respective trajectory. The Kalman filter algorithm reaches the target after a covered distance of 6.5 km with an accuracy of 3.5%, the algorithm using the compass shows an error of twice the size, and the results of the algorithm that uses the gyroscope data only are not satisfactory at all.

It can be seen that the algorithms using the compass are better in keeping the orientation than the algorithm using incremental information only. Orientation is lost right at the beginning of the drive, afterwards the vehicle is steadily turning too far to the right.

Reasons for the superior performance of the Kalman algorithm in comparison to the simple use of the compass data can be explained using *Fig. 10*. The orientation information of the compass alone is plotted as a dashed line, while the orientation for the Kalman algorithm is plotted as

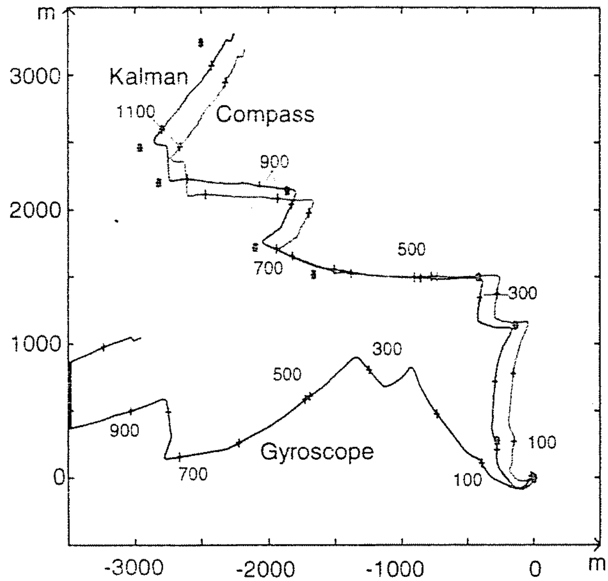

Fig. 9. In-town test Drive

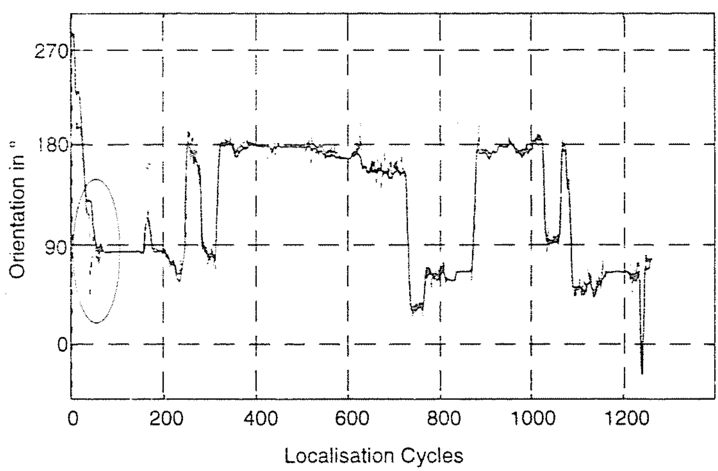

Fig. 10. Kalman filter and compass orientation for test drive

solid line. The angle information of the compass suffers from short-time disturbances. At the beginning of the track, the road crossed railway lines close to the central station of Karlsruhe. This leads to massive disturbances in the compass data. The orientation determined by the Kalman algorithm does not follow the compass data because of the use of additional data from the incremental sensors.

More test drives show similar results. Still it shows that preprocessing of the sensor data is most important to achieve satisfactory results. If, for example, the medium and long-term errors of the magnetic field probe are not compensated properly, the estimated orientation has a bias of several degrees. This leads to significant localisation errors.

6. Conclusions

A method for autonomous localisation of vehicles based on wheel rotation measurement, yaw rate measurement and a compass was presented. The determination of the covered distance is performed based solely on the wheel information, while the orientation of the vehicle is determined based on all available sensors. Combination of the sensor data is performed using cascaded Kalman filters. Modelling of the sensor errors gives the possibility for adaptive variation of the noise variances used to calculate the Kalman filter gain. So, an improved estimation for the vehicles orientation can be achieved.

A careful pre-processing of the sensor data is very important. Special care must be taken considering the compensation of the offset drift of the compass. Badly compensated compass data deteriorates the function of the localisation system remarkably.

Development of algorithms to improve estimation of the covered distance are subject of further investigations as well as map-matching methods. This will not only provide the opportunity for global localisation but also the possibility to adopt parameters which are subject to change during operation of the vehicle. Mainly, that are the wheel diameters and the offset drift of the gyroscope. Methods to improve compass compensation are also investigated.

The localisation system presented is implemented in real-time in a test vehicle at the Institute for Industrial Information Systems at the University of Karlsruhe.

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