Estimation of Vehicle Speed
Fuzzy-Estimation in Comparison with Kalman-Filtering

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Abstract: Aim of the presented system is to measure the wheel slip with an accuracy of 1% without using expensive sensors. Therefore a multisensor data fusion is used with the integration of the commonly used ABS wheel speed sensors. Two approaches are compared whereby the Fuzzy approach is new and the Kalman approach is taken from the literature. Furthermore the possibility of estimating the road slope with this system is shown.

1 Introduction

Coming spring a new generation of Antilock Braking Systems will appear with the capability of stabilising the car during cornering (vehicle dynamics control). Therefore the vehicle speed over ground has to be measured very exactly. Until now the velocity is measured with inductive sensors for the wheel rotational speed. With the occurrence of longitudinal or side slip these sensors can not provide sufficient informations to control vehicle dynamic.

There are several methods of measuring vehicle speed. Optical or microwave sensors use a correlation method where highly accurate measurements are possible, however these sensors are very expensive and will not be used for ABS.

Therefore an estimation system is necessary which combines the results of the wheel speed sensors with another less expensive speed measuring sensor. As during normal driving conditions the ABS wheel speed sensors provide very accurate information an acceleration sensor is chosen. This sensor can deliver speed information only during short time periods but this is sufficient during acceleration or braking transients.

The method of data fusion with Kalman-Filtering /1/ is summarised and a new approach with Fuzzy-Logic is shown. The behaviour of the different wheel speeds during cornering is considered by a correction term dependent on the actual yaw rate, i.e. for the front left wheel (b_F is the axe length) :

$$v_{\mathrm{FL}} = v_{\mathrm{FLmeasure}} + \dot{\psi} \cdot \frac{b_{\mathrm{F}}}{2} \qquad (1)$$

2. Measurement System

As described before the estimation system is based upon multisensor data fusion, that means several sensors are used to measure the vehicle speed and the Estimator decides which sensor is most reliable. The sensor configuration is shown in figure 1:

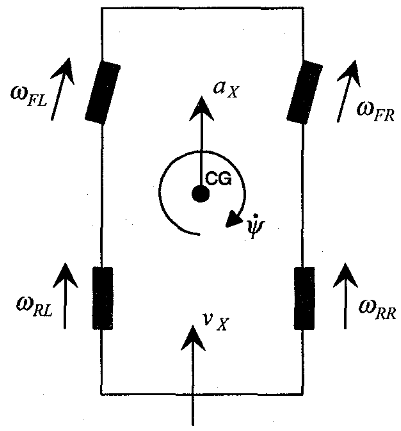

Figure 1 : Sensor configuration for the speed estimation

For each wheel the well-known ABS wheel speed sensors are used, an acceleration sensor for longitudinal acceleration and a gyroscope to measure the yaw rate. The yaw rate is used in (1) to determine the actual curve radius for correcting the wheel speeds, that means by (1) the wheel speeds are transformed to the centre of gravity. For reference purposes an optical speed over ground measuring system is used, also shown in figure 1.

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3 Fuzzy-System

Figure 2 shows the schematic structure of the Fuzzy-Estimator. The measured data are first analog filtered with bessel low pass filters to obtain small phase shift. Then a data preprocessing block is used to calculate the input values for the Fuzzy Logic. The preprocessing formulas are a combination of slip and acceleration calculation (2, 3). Using a sampling rate of 10 msec the inputs are very close to the real slip values.

$$delta\_v_i(k) = \frac{\omega_i(k)\cdot r_{Wheel} - v_{Fuz}(k-1)}{v_{Fuz}(k-1)}\cdot 100\% \quad (2)$$

The input $delta\_v_A$ is calculated by :

$$delta\_v_A(k) = \frac{\left(a_X(k) - a_{Offset}(k)\right)\cdot T_S}{v_{Fuz}(k-1)}\cdot 100\%, \quad (3)$$

whereby a_{Offset} is a correction value consisting of an offset and a road slope part. v_A is the speed calculated from acceleration. The preprocessing unit also uses the estimated velocity of the previous cycle $v_{Fuz}(k-1)$.

The offset error a_{Offset} of the acceleration sensor is derived by comparing the vehicle speed calculated with Fuzzy-Logic-System v_{Fuz} with the integral of the acceleration sensor. During normal driving conditions, that means small longitudinal and lateral acceleration values, the wheel speed sensors are very accurate. Comparing v_{Fuz} and the integral of a_X an estimation of the road slope is possible and shown in chapter 5.

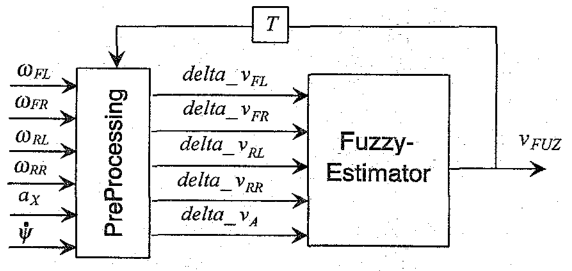

Figure 2 : Estimation of the car velocity.

The Fuzzy-Estimator itself is devided into two parts, the first determines which wheel is most reliable and the second

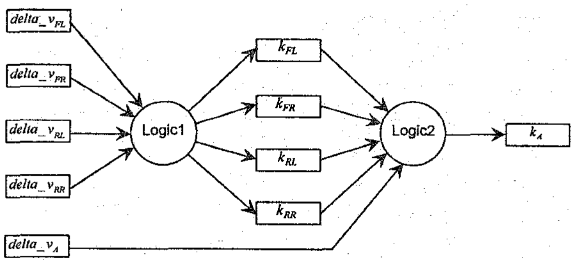

Figure 3 : Structure of the Fuzzy-Estimator.

decides about the reliability of the integral of the acceleration sensor, shown in Figure 3.

This cascade structure is chosen to reduce the number of rules. A fully occupied matrix in the Rule table will result in 1024 rules. Using the cascade structure lots of rules can be saved. The wheel radius used in (2) are set to constant values. The change of wheel radius are only several permille /6/. As the wheel speeds and the car velocity changes nearly the same shape the mistakes in using a wrong wheel radius are neglectable.

The Fuzzy rule table is very sparsely occupied. For the first Logic rule table only 34 of the possible 256 rules are used and for the second Logic the table is even more sparsely occupied. Logic2 consists of only 10 rules. Utilising so few rules the Fuzzy-Estimator is very suitable for on-line vehicle control, i.e. an ABS control loop.

The output is derived as a weighted sum of the wheel measurements plus the integrated and corrected acceleration:

$$v_{Fuz}(k) = \frac{\sum_{i=1}^{4} k_i\,\omega_i(k) r_{Wheel} + k_A\left(\left(a_X(k) - a_{Cor}(k)\right)\cdot T_S + v_{Fuz}(k-1)\right)}{k_A + \sum_{i=1}^{4} k_i} \quad (4)$$

The linguistic variables and the rule table are designed without a numerical optimisation. They are created by having a close look at the measured data during ABS Braking action. The input Fuzzyfication is shown in figure 4 and the output Defuzzyfication in figure 5. Four linguistic variables are used for the inputs and for the outputs three are sufficient.

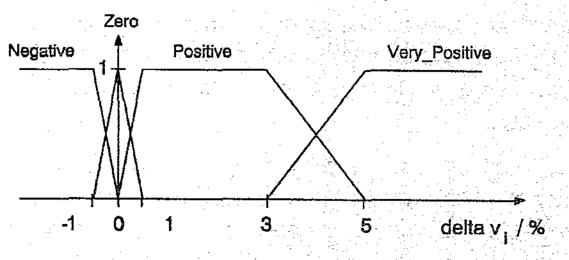

Figure 4 : Fuzzyfication.

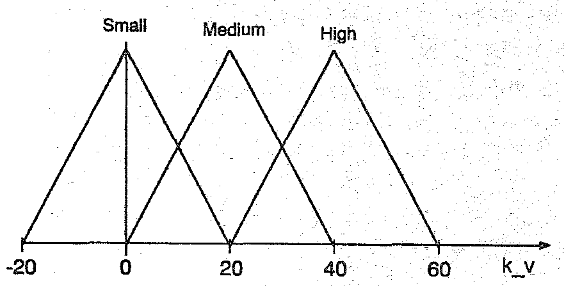

Figure 5 : Defuzzyfication.

4 Estimation Results using Fuzzy-Logic

The Fuzzy system was designed using measured data of a testcar. The testcar was equipped with the sensors shown in figure 1. After designing the system off line with measured data, the estimation system was implemented on a micro controller and tested on-line. The results are nearly the same. The experimental platform contains a micro controller similar to the SAB 80C51 and therefore the sampling time has to be increased to 16ms.

To compare Fuzzy-Logic with Kalman-Filtering the results of the off-line calculation are shown.

Figure 6 shows the non filtered sampled data of all sensors with the exception that the acceleration was integrated. The test-drive was made on a snow-covered road with curves. The two braking transients are both ABS controlled. The last part of the course the road has a climbing angle.

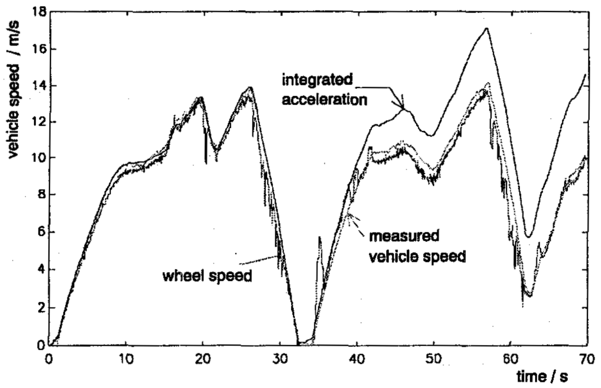

Figure 6 : Non filtered measured data.

Applying these data to the Fuzzy Estimator and comparing the reference speed to the estimated speed the high quality of the estimation results can be seen in figure 7. The estimated vehicle speed is hardly be distinguishable from the measured speed.

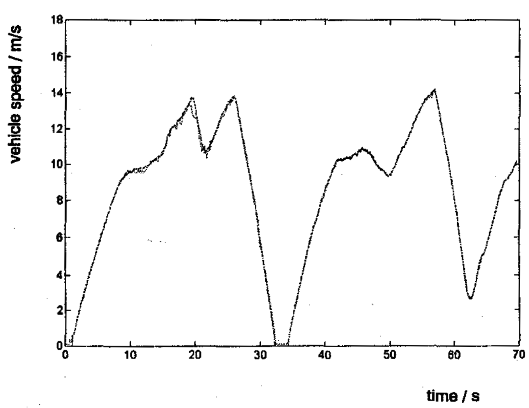

Figure 7 : Reference and estimated car velocity.

5 Correction of Acceleration

During driving on roads with climbing angle the offset error of the accelerating sensor can be calculated with a Moving Average Filter over two seconds :

$$a_{Offset} = \frac{v_{Fuz1}(k+200) - v_{Fuz1}(k+1)}{200 \cdot T_S} - \frac{1}{200}\sum_{i=1}^{200} a_X(k+i) \tag{5}$$

With the assumption that the offset error of the sensor is small against the error caused by the road slope, the slope can be calculated by :

$$\alpha_{Slope} = \arcsin\left(\frac{a_{Offset}}{g}\right) \tag{6}$$

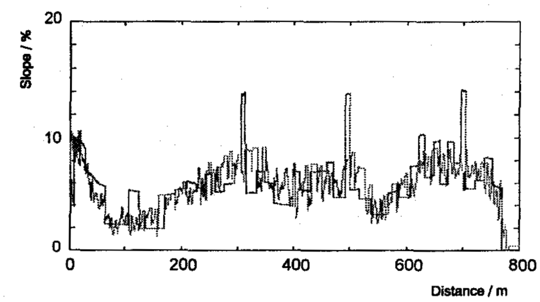

Figure 8 : Estimated and measured road slope.

The reference road slope is calculated with a pressure sensor, which has a resolution of 1 m. Therefore the reference slope is badly quantified. Figure 8 shows the excellent results of estimating the road slope. The additional acceleration sensor can provide this important information which is not only suitable for Antilock Braking Systems.

Therefore the assumption, that most part of the offset error is caused by road slope, is right. Figure 8 is based on another test course which has a greater climbing angle and a drive without ABS controlled braking transients.

6 Kalman-Filter

Kalman-Filter technique is based upon a state space model :

$$\begin{aligned} \mathbf{x}(k+1) &= \mathbf{A}(k)\mathbf{x}(k) + \mathbf{B}(k)\mathbf{u}(k) \\ \mathbf{y}(k) &= \mathbf{C}(k)\mathbf{x}(k) + \mathbf{n}(k) \end{aligned} \quad , \tag{7}$$

whereby **x**(k) is the state- , **y**(k) is the measurement-, **u**(k) is the input- and **n**(k) is the noise vector. In this case a signal model is needed, so that the inputs are modelled as white noise.

$$\begin{bmatrix} am \\ vm_1 \\ vm_2 \\ vm_3 \\ vm_4 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} a_x \\ v_x \end{bmatrix} + \begin{bmatrix} n_a \\ n_1 \\ n_2 \\ n_3 \\ n_4 \end{bmatrix} \quad (8)$$

$$\begin{bmatrix} \dot{a}_x \\ \dot{v}_x \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ T & 1 \end{bmatrix} \begin{bmatrix} a_x \\ v_x \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \quad (9)$$

The structure of the Kalman-Estimator is shown in figure 9. $\mathbf{R}(k)$ is the gain matrix which has to be calculated recursively, see (8,9).

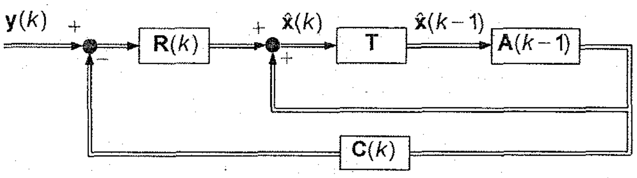

Figure 9 : Structure of the Kalman-Estimator.

The formula for the gain matrix is taken of /4/ :

gain matrix:

$$\mathbf{R}(k) = \mathbf{S}_{ee}(k)\mathbf{C}^T(k)\left[\mathbf{V}_n(k) + \mathbf{C}(k)\mathbf{S}_{ee}(k)\mathbf{C}^T(k)\right]^{-1} \quad (10)$$

$\mathbf{S}_{ee}(k)$ recursion:

$$f(\mathbf{A}(k), \mathbf{R}(k), \mathbf{C}(k), \mathbf{B}(k), \mathbf{V}_u(k), \mathbf{S}_{ee}(k-1)) \quad (11)$$

The covariance matrices $\mathbf{V}_n(k)$ and $\mathbf{V}_u(k)$ are calculated depending of the actual driving situation. The trick of this system is that these covariance matrices are changed based on a rule system. For example two rules :

> If the acceleration is positive high, then the noise of the front wheel speeds is small.
>
> If the wheel slip is negative high, then the noise of the acceleration signal is small.

Figure 9 shows the results of the Kalman-Filter for the same test drive than in figure 6 and 7. The estimated velocity looks equally to the Fuzzy one. Chapter 7 will have a closer look at the estimation errors.

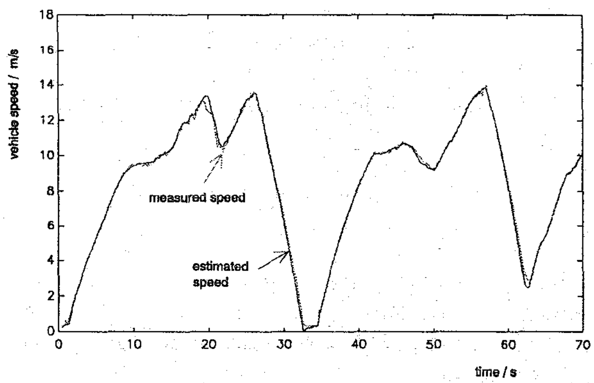

Figure 9 : Reference and estimated car velocity.

For the calculation of the gain matrix $\mathbf{R}(k)$ an Inversion of a (5,5) matrix is necessary. Therefore no real-time implementation on a common used micro controller is possible.

7 Comparison of different approaches

To enable a more precise comparison between the two Estimators the estimation error is shown in figure 10. Both Estimators show even in this high resolution results of high quality.

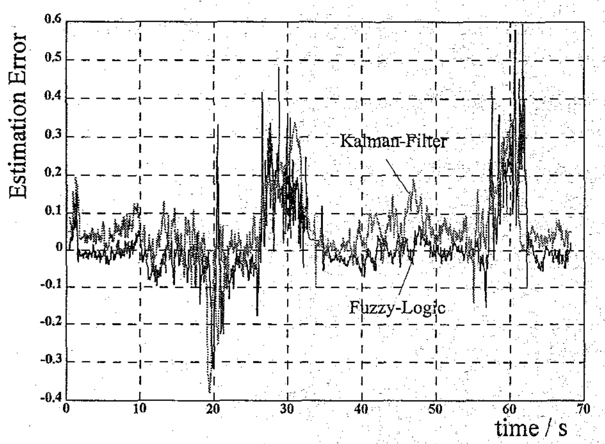

Figure 10 : Estimation error of both systems.

Considering only the quality of the estimation results both Estimators seem to be equal. It is obvious that the Fuzzy system can be implemented within a common used ABS micro controller. But to my opinion the Fuzzy System has even more advantages: It is more easy to design and to improve a special driving situation. Beyond that a lot of research is in progress to optimize Fuzzy Systems /7/, which will enhance furthermore the estimation quality.

8 Literature

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