Vehicle System Dynamics, 27 (1997), pp. 477–489
0042-3114/97/2705-477$12.00

Fuzzy Approach to the Real Time Longitudinal Velocity Estimation of a FWD Car in Critical Situations

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SUMMARY

This paper presents a new approach to the fuzzy estimation of the variables of complex, fast, closed-loop systems. It is used to develop an original real-time longitudinal velocity estimator for FWD cars. Its application covers highly critical driving situations and avoids the use of an expensive optical cross-correlation sensor. The aim is to provide vehicle monitoring processes with a reliable value of the longitudinal velocity. Fuzzy aggregate indicators are used to identify and detect the different ways a vehicle behaves. Then, a fuzzy expert system with rules based on these indicators decides which values should be used among those which allow the estimation of the longitudinal velocity.

1. INTRODUCTION

Active safety has become very important in automotive systems due to the user's requests. So, research projects are being pursued on vehicle braking control systems, fault diagnosis, and vehicle monitoring processes. To obtain greater accuracy in the development of a car supervisor for instance, the estimation of built-in variables is very important because of the application costs. In critical situations built-in parameters allow a better vehicle behaviour estimation and the elimination of wrong fault detections. In the case of complex systems, a fuzzy logic estimator is often an efficient tool to provide good results with reduced designing time.

A good understanding of real-time longitudinal velocity would be helpful for many of these applications. However, according to car manufacturers, the estimate of longitudinal velocity should only be performed with a minimum of additional measured variables. Moreover, the sensors have to be inexpensive. In the literature, results have been reported which provide, in most situations, a good

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estimation of the longitudinal velocity; but critical situations often give poor results. The results presented in this paper aim at responding to such critical situations with increased accuracy compared with classic methods for a FWD vehicle.

For a FWD car, the methods which are most commonly used compute their estimation by averaging the wheel speed values or taking account of the maximum value of the driven wheel speeds. Unfortunately, for this kind of vehicle, the front wheel velocities are often disturbed in some cases, such as: acceleration cycle, braking cycle, and so forth. Acceleration sensors are added to take the longitudinal acceleration into account and to cover the lapses of time when the information given by the wheels is not reliable. But the measurements are so noisy and calibration so inaccurate that a simple integration is unusable. Even complex methods, like the tuned Kalman filter developed by K. Watanabe, K. Kobayashi and C. Cheok [1] do not provide a satisfactory solution for calibration issues. It must be noted that the covariance matrix of the Kalman filter was tuned by rules to distinguish several driving situations.

Kosko [3] reported results that show similar performance for Kalman filter and fuzzy logic; that is why the latter was chosen.

2. LIST OF SYMBOLS

Code	**Unit**	**Meaning**
Vr	m/s	longitudinal velocity reference
Vlr	m/s	lateral velocity reference
ν_{fl}	m/s	front left wheel longitudinal velocity
ν_{fr}	m/s	front right wheel longitudinal velocity
ν_{rl}	m/s	rear left wheel longitudinal velocity
ν_{rr}	m/s	rear right wheel longitudinal velocity
γ_L	m/s^2	longitudinal acceleration
γ_T	m/s^2	lateral acceleration
α_V	degree	steering wheel angle
$\dot{\psi}$	degree/s	yaw rate

3. MEASUREMENTS

3.1. Designation of Critical Situations

To create critical situations with a FWD vehicle, different experiments were carried out with the instrumented laboratory car. Different test tracks were used, as

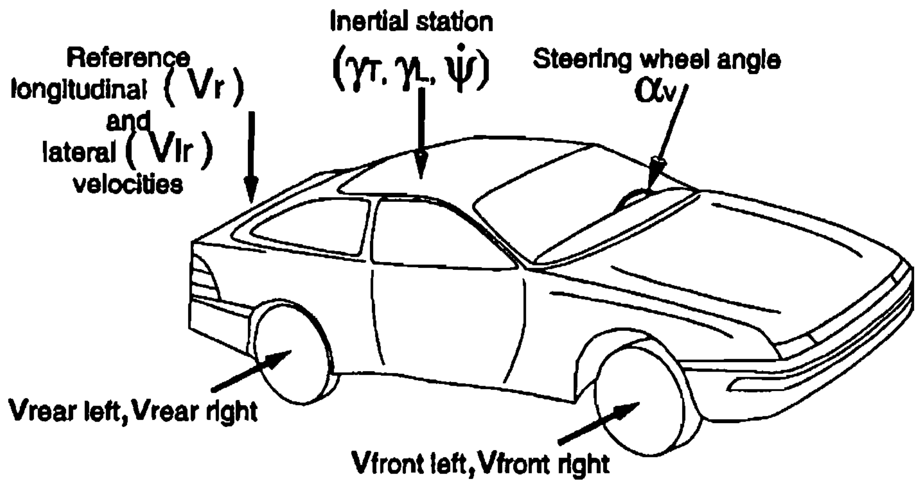

Fig. 1. Sensors and measurement parameters in the test car.

will be shown below. The different sensors and measurement parameters needed in the test car for these trials are shown in Fig. 1.

The reference longitudinal and lateral velocities are measured by an optical cross-correlation sensor, located at the rear centre of the vehicle. The signals of the different wheel velocities (pulses) are taken from the ABS-system. The gyro and acceleration sensors are located near the centre of gravity of the test car.

All the signals are digitized by a data acquisition card inside a PC computer at the back of the test car.

3.2. Longitudinal Velocity Estimation

As stated before, the number of sensors must be reduced to a minimum so as to meet the financial and feasibility requirements of the industry. For the real-time estimation of the longitudinal velocity with the present fuzzy expert system, the vehicle velocity (the velocity of the four vehicle wheels), the steering angle, the longitudinal and lateral accelerations and the yaw rate are measured.

4. DEFINITION OF THE CRITICAL SITUATIONS TO BE DETECTED

According to the critical situations the representative driver of a FWD car can meet with, the different cases that the estimator has to cover are selected. These critical driving conditions are specified below.

4.1. Foot off the Accelerator while Cornering

This situation generally occurs when a driver drives too fast at the beginning of a bend. He may then react in lifting his foot from the accelerator pedal while cornering. Near the grip limit, depending on the road conditions, vehicle speed and steering wheel value, the situation is considered as critical. This happens more frequently when the grip limit is lower on wet and icy roads because of the driver's behaviour [4].

Experiments
Several experiments were carried out on a wet test track to highlight this phenomenon. At first, the vehicle was driven straight on, then into a 90-degree curve while the driver steered and simultaneously jumped off the accelerator pedal.

4.2. Dissymmetrical Braking

Dissymmetrical braking may occur especially on icy roads, when grip conditions are irregular.
Experiments
A 0.8 m wide low grip (the friction coefficient is near 0.5) straight line was drawn on a straight dry road to simulate dissymmetrical icy conditions.

4.3. Violent Braking while Cornering

If the driver brakes sharply in an emergency while cornering, the inner front wheel may lock, and the rear one may no longer adhere to the road. Both inner wheels may lose their contact with the road if the driver takes a bend 'on two wheels'. As shown in Fig. 2, the velocity values computed on the inner wheel speeds are not reliable in these cases.
Experiments
Several tests were carried out on a dry normal road. At first, the vehicle was driven straight on; then the driver suddenly steered and braked violently.

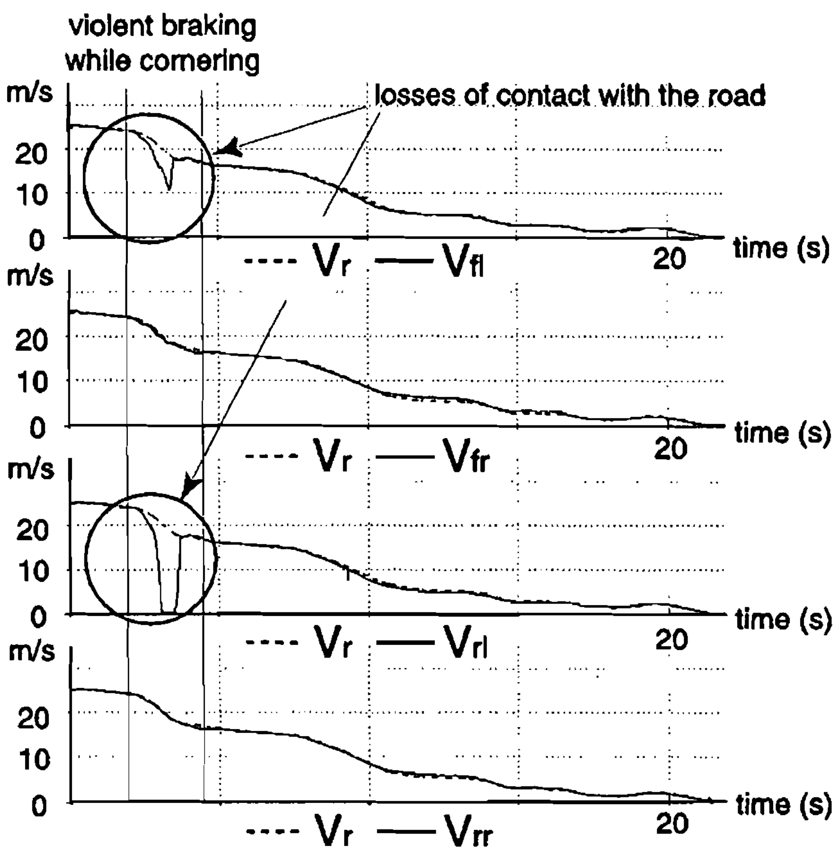

Fig. 2. Violent braking while cornering to the left. Front and rear left wheels tend to lock.

FUZZY APPROACH TO VELOCITY ESTIMATION ...

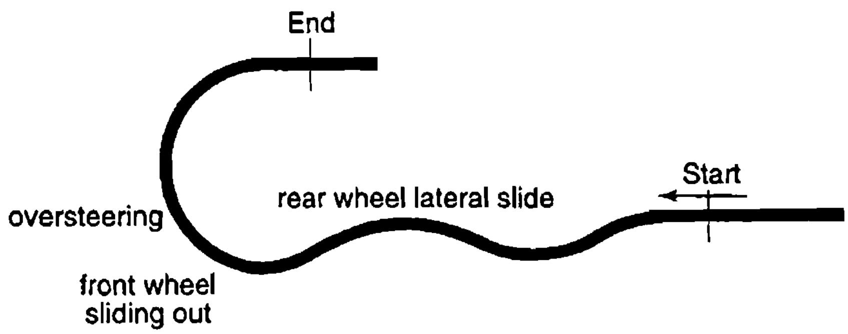

Fig. 3. Top view of the test track.

4.4. Oversteering, Front Wheel Sliding-Out and Lateral Sliding

Such FWD vehicle behaviours are other classic examples of critical situations.

- Oversteering occurs when the vehicle becomes unstable with rear wheel lateral slide. The driver tries to compensate for the deviation of the vehicle from the normally expected trajectory by steering into the skid.
- Front wheel sliding-out generally occurs when taking a sharp bend at a high speed.
- Lateral sliding generally occurs when a driver drives too fast into a wide curve near the grip limit.

Experiments

These were the most complex and dangerous situations to recreate. A test driver was asked to simulate them. When entering the curve, the driver used the hand brake to induce oversteering, steered into the skid, and accelerated to compensate for the front slip. For a lapse of time, none of the wheel velocities were reliable: the rear wheels were locked, and the front wheels skidded (Fig. 3).

A wide set of experiments were carried out on different test tracks in various driving situations. Some highly critical ones proved the above mentioned methods to be unusable. In particular, some phenomena may invalidate an estimator using an average rear wheel speed value, which is otherwise very efficient for a FWD car.

According to the measurements, averaging the rear wheel speed values remains acceptable for dissymmetrical braking. The other cases require an enhanced estimator.

5. DETECTING THE VEHICLE BEHAVIOUR

For this application, the first main target was to identify and detect the different ways in which a vehicle behaves. To improve the efficiency of the estimator, a method had to be perfected to identify and detect the phenomena that invalidate the rear wheel speed values. As will be shown below, fuzzy logic can be used to aggregate the data in order to build indicators for the different types of vehicle behaviour. Two indicators are operational so far.

Simulations were carried out to find the best compromise between a satisfactory sensitivity of the indicators and the complexity of the inference system which is to be real-time implemented. They show that either triangular or trapezoid shapes can be used, and that Sugeno's and Mamdani's inference methods lead to similar responses to the driving situations. Normed trapezoid fuzzy sets and Mamdani's inference method were eventually chosen.

5.1. Loss of Contact while Cornering: I_{lc}

The aim of the aggregate indicator I_{lc} is to detect the cases when the wheel loses its contact with the road. The rules of this indicator are based on the two following measured variables:

$$\gamma_T \text{ and } \dot{\psi}$$

The I_{lc} indicator tells the longitudinal velocity fuzzy estimator which rules must be used.

In both cases mentioned in 4.3, the lateral acceleration γ_T can reach high values. But according to the measurements, γ_T can be high without any rear wheel locking. This actually occurs with a high yaw rate, in a tight curve. Hence the development of a fuzzy indicator builder using the five following rules:

- If γ_T is nil and $\dot{\psi}$ is nil then I_{lc} is nil
- If γ_T is positive and $\dot{\psi}$ is nil then I_{lc} is positive
- If γ_T is negative and $\dot{\psi}$ is nil then I_{lc} is negative
- If $\dot{\psi}$ is positive then I_{lc} is nil
- If $\dot{\psi}$ is negative then I_{lc} is nil

where *nil*, *positive*, *negative* are fuzzy sets, in accordance with the concept introduced by Zadeh in 1965 [2].

A non-zero value for I_{lc} detects the possibility for a rear wheel to lose its contact with the road. With the co-ordinate system, a negative value is associated with the left rear wheel, and a positive value with the right one.

5.2. Oversteering, Front Wheel Sliding-Out and Lateral Sliding: I_{ols}

This second indicator I_{ols} detects critical deviations from the intended driving behaviour of the vehicle during lateral motion. This indicator particularly highlights front wheel sliding-out and rear wheel lateral slide situations. Measurements and simulations show that this situation can be detected as long as it lasts, by considering the variables:

$$\alpha_V,\ \gamma_T,\ \ddot{\psi},\ \text{and}\ \dot{\gamma}_T.$$

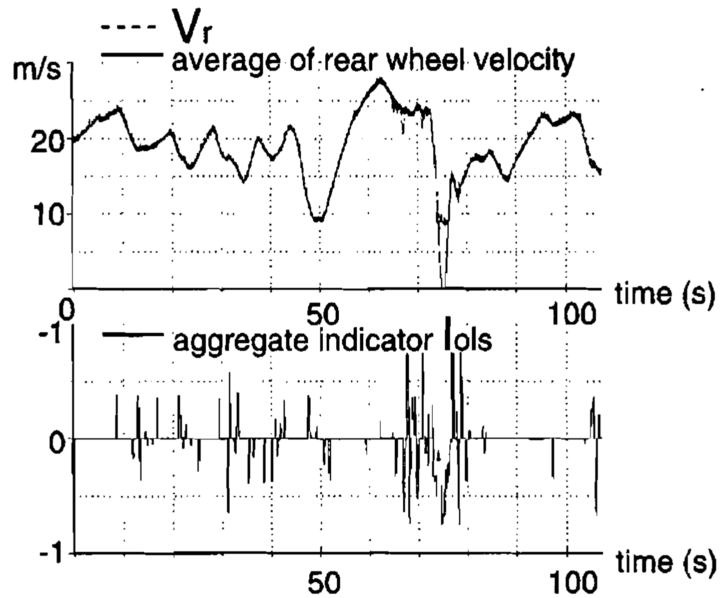

Fig. 4. I_{ols} indicator results for a general vehicle behaviour test.

I_{ols} is then used by the longitudinal velocity fuzzy estimator to indicate which rules must be used.

The fuzzy builder of this indicator uses the eleven following rules:

- If $\ddot{\psi}$ is nil and $\dot{\gamma}_T$ is nil then I_{ols} is nil
- If $\ddot{\psi}$ is negative and $\dot{\gamma}_T$ is negative then I_{ols} is nil
- If $\ddot{\psi}$ is positive and $\dot{\gamma}_T$ is positive then I_{ols} is nil
- If γ_T is positive and α_V is positive then I_{ols} is nil
- If γ_T is negative and α_V is negative then I_{ols} is nil
- If $\ddot{\psi}$ is negative and $\dot{\gamma}_T$ is nil then I_{ols} is negative
- If $\ddot{\psi}$ is negative and $\dot{\gamma}_T$ is positive then I_{ols} is negative
- If γ_T is positive and α_V is negative then I_{ols} is negative
- If $\ddot{\psi}$ is positive and $\dot{\gamma}_T$ is nil then I_{ols} is positive
- If $\ddot{\psi}$ is positive and $\dot{\gamma}_T$ is negative then I_{ols} is positive
- If γ_T is negative and α_V is positive then I_{ols} is positive

where *nil*, *positive*, *negative* are normed, trapezoid fuzzy sets. The rules using γ_T and α_V compare the response of the vehicle in lateral acceleration to the steering angle input.

The present indicator highlights sliding situations that appear on the behaviour trial shown in Fig. 4. It is complementary to the loss-of-contact indicator (I_{lc}).

6. FUZZY ESTIMATION OF THE LONGITUDINAL VELOCITY

Fig. 5 shows the general structure of the longitudinal velocity fuzzy estimator. Indicators I_{lc} and I_{ols} are used to identify the troubled vehicle behaviour (de-

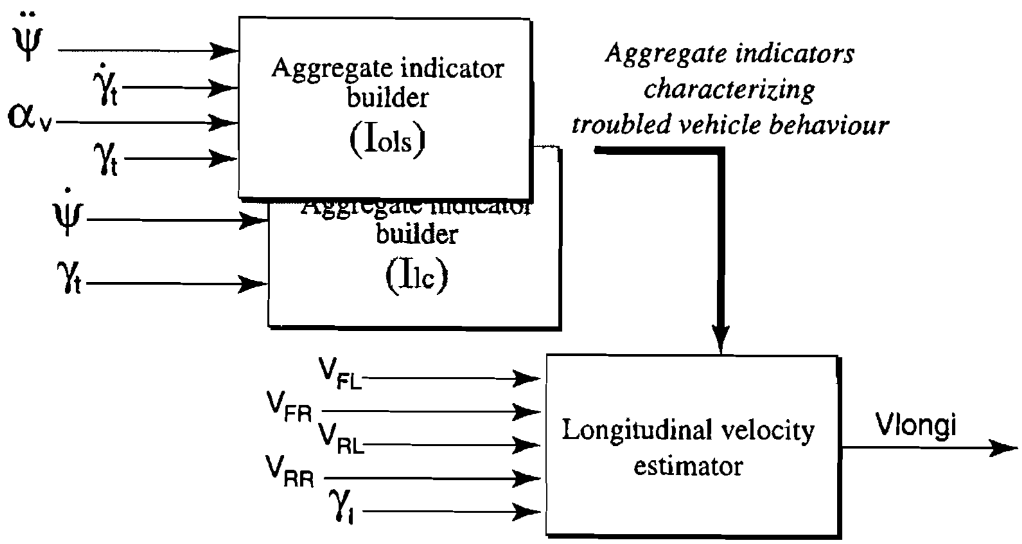

Fig. 5. General structure of the fuzzy expert system estimating the vehicle's longitudinal velocity of the vehicle.

scribed before). According to the driving situation, a fuzzy expert system will choose the best combination of the available 'primary' estimations.

6.1. Primary Estimations

They are computed with the variables which are likely to contain most of the information about the longitudinal velocity. So, it is necessary to specify that the study only regards the FWD vehicle. Indeed, considering the rear-wheel driven vehicle behaviour, critical situations occur for complex conditions [5]. This would require a specific study of the longitudinal velocity estimate.

For a FWD vehicle, the measurements of the front wheel rotation speed is generally disturbed during accelerations. And when braked, depending on the right control of the brake effort proportioning system, front wheels tend to lock more often than rear wheels. With an ABS braking system, the measurement problems are due to partial losses of grip and resumptions. That is why the implication of the front wheel rotation speed in the evaluation was limited.

In most normal cases, the average of the rear wheel velocities or the maximum value of driven wheel speeds give a good estimation of the longitudinal velocity. For the situations detected by the indicators, primary estimations are the two rear wheel speed values, crossed front-rear averages of wheel speed values and the integral of the longitudinal acceleration. Unfortunately, the latter tends to diverge and is not reliable.

6.2. Structure of the Fuzzy Expert System

As the expert system has to mix different available functions, the conclusions of the rules are procedural and the Sugeno style method was used. Furthermore, the Sugeno inference system gives non fuzzy results and the defuzzyfication interface is virtual for this estimator.

Simulations were carried out to find the best compromise between a satisfactory accuracy of the longitudinal speed estimation and the complexity of the inference system to be real-time implemented. Just as for the builders of indicators, the specifications of degrees of truth for each variable in the system involved normed trapezoid shapes. The number of fuzzy sets for each variable was set to three: negative, nil, and positive. The values defining the fuzzy sets were determined relatively to the information and understanding about the road vehicle.

6.3. Rules

Experiments suggested that taking account of the integral of the longitudinal acceleration was not necessary in the situations encountered. Two sets of five rules were established to compare the two methods.

Using the rotation speeds of the wheels only:

- If I_{ols} is positive then $\nu_{estimated} = (\nu_{fr} + \nu_{rl}/2)$
- If I_{ols} is negative then $\nu_{estimated} = (\nu_{fl} + \nu_{rr}/2)$
- If I_{lc} is positive then $\nu_{estimated} = \nu_{fl}$
- If I_{lc} is negative then $\nu_{estimated} = \nu_{fr}$
- If I_{lc} is nil then $\nu_{estimated} = (\nu_{rl} + \nu_{rr}/2)$

Using the integral of the longitudinal acceleration:

- If I_{ols} is positive then $\nu_{estimated} = \nu_{k-1} + \int_{t_{k-1}}^{t_k} \gamma_L dt$
- If I_{ols} is negative then $\nu_{estimated} = \nu_{k-1} + \int_{t_{k-1}}^{t_k} \gamma_L dt$
- If I_{ols} is nil and I_{lc} is positive then $\nu_{estimated} = \nu_{rl}$
- If I_{ols} is nil and I_{lc} is negative then $\nu_{estimated} = \nu_{rr}$
- If I_{ols} is nil and I_{lc} is nil then $\nu_{estimated} = (\nu_{rl} + \nu_{rr}/2)$

7. ESTIMATION RESULTS

The results of the experiments are shown in Figs. 6–10. They were obtained with the test car described in Fig. 1. All the driving situations encountered in the trials were submitted to the estimator. This paper only describes the most critical ones.

7.1. Foot off the Accelerator

As shown in Fig. 6, the estimator provides an improvement in comparison with a simple averaging of the rear wheel speed values, at the crucial time when the car becomes uncontrollable for a non expert driver.

7.2. Violent Braking while Cornering

The indicator Ilc detects losses of contact and allows the fuzzy expert system to choose the best rear wheel speed value (Fig. 7). Then, for this critical situation, the results of the longitudinal velocity fuzzy estimator and those obtained by taking the maximum value of driven wheel speeds are similar.

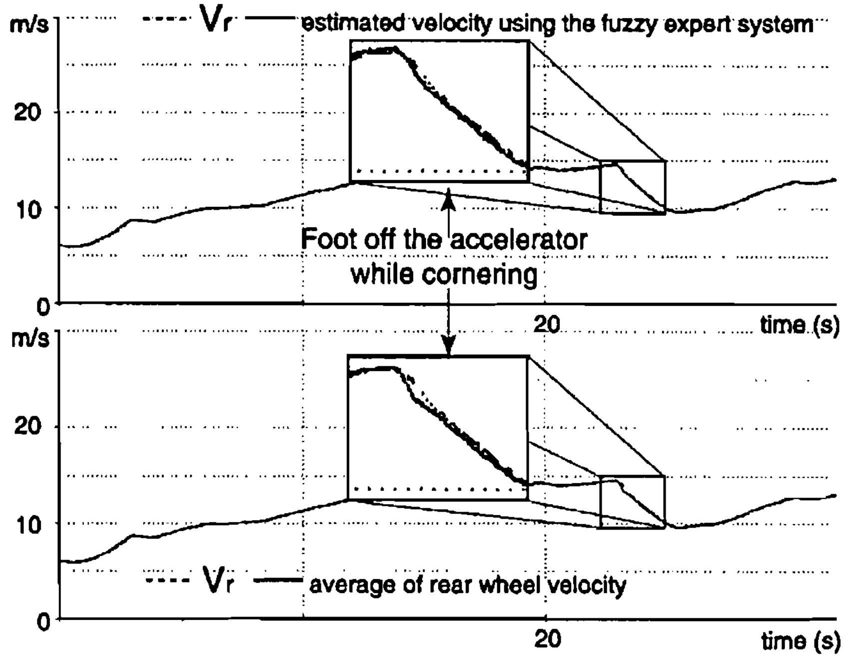

Fig. 6. Comparison of results for a test cycle on a wet road in "foot off the accelerator position" while cornering to the right.

7.3. Oversteering, Front Wheel Sliding-Out and Lateral Sliding

The two methods mentioned in section 6.3 are compared through the following results in the case of front wheel sliding-out and simultaneous oversteering and lateral sliding.

Using the Wheel Speeds Only

These results shown in Fig. 8 illustrate the power of fuzzy logic for the study of complex systems, when conventional modelling is impossible. Indeed, in such a

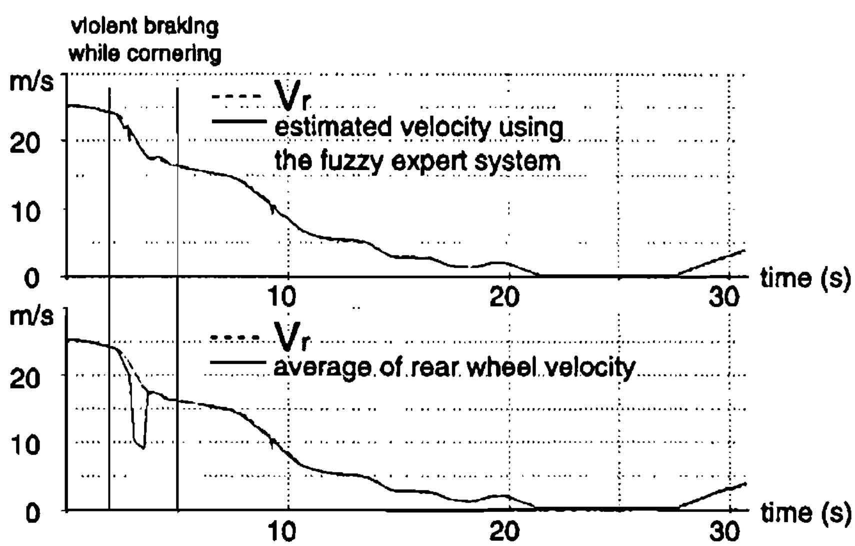

Fig. 7. Comparison of results for a violent braking cycle while cornering.

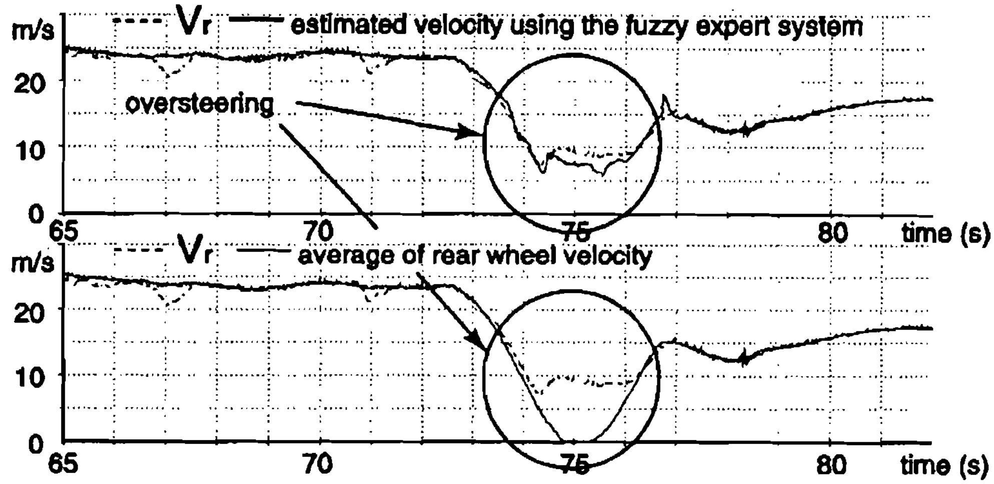

Fig. 8. Comparison of results with the fuzzy estimator using the wheel speed only.

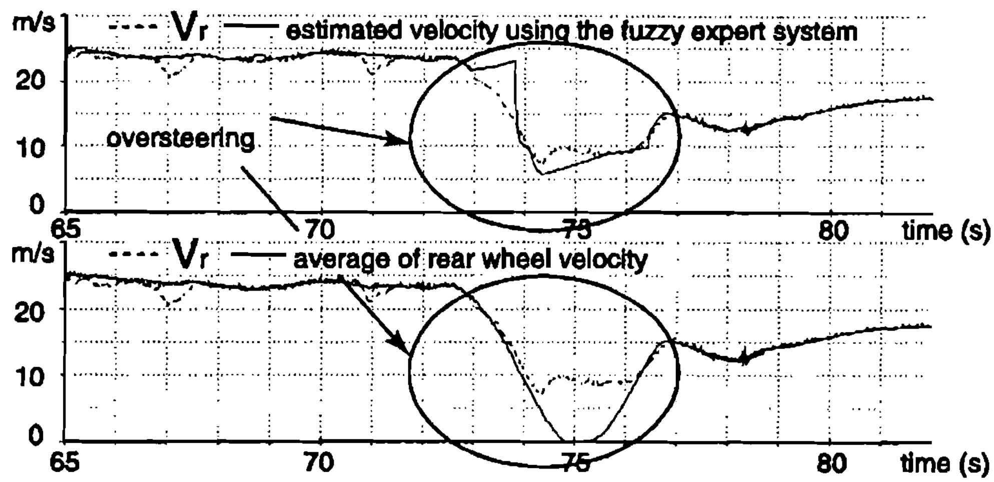

Fig. 9. Comparison of results with the fuzzy estimator using the integral of the longitudinal acceleration.

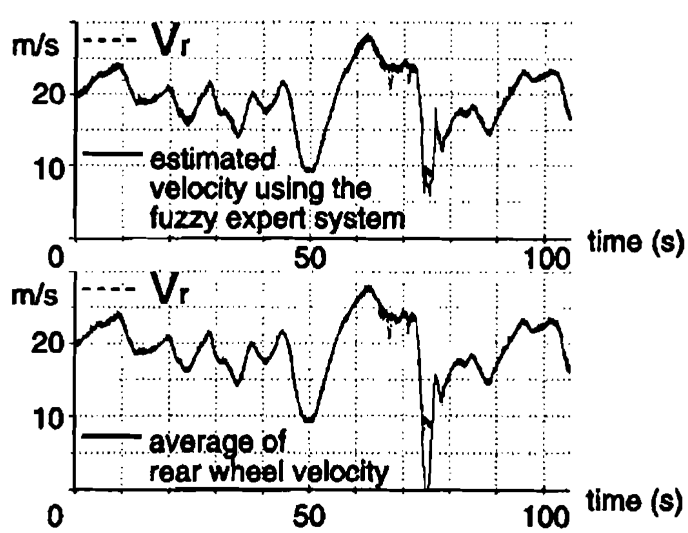

Fig. 10. Comparison of results for a general vehicle behaviour test which implies lateral sliding and oversteering situations.

situation, a model of the vehicle would involve unknown or unsteady variables like grip conditions.

Integrating the Acceleration.
This result (Fig. 9) illustrates the difficulty encountered when using the longitudinal acceleration sensor. Noise and calibration issues account for this bad performance. The idea could thus be useful for some so far untested situations.

Finally, Fig. 10 shows the longitudinal velocity estimate compared with the average of the rear wheel velocity. According to the experimental conditions defined previously (Fig. 3), front wheel sliding-out, lateral sliding and oversteering situations were tested.

8. DISCUSSION

An application study of a FWD car has been investigated. Due to time-consuming constraints, the inference system complexity was deliberately limited (builders of aggregate indicators and estimator). However, it was shown that in the critical situations encountered by the common driver, the estimator provided better results than classic methods such as the average of rear wheel speed or the utilization of the Kalman filter.

Only two indicators of vehicle behaviour are operational, but they cover the most dangerous situations. Other indicators are under study to optimise the fuzzy estimator for all driving cases. For the present, the longitudinal velocity fuzzy estimator has not been studied for a rear-wheel driven vehicle. Due to the typical behaviour of this kind of vehicle, these aggregate indicators will probably not work and should be modified. In the same manner, the rules of the fuzzy estimator should be modified.

The understanding of the complete real-time velocity vector using only cheap sensors is interesting for most vehicle monitoring processes. An increased robustness of these algorithms could be obtained without any expensive optical cross correlation sensor. This would allow car manufacturers to generalise the use of vehicle monitoring processes.

Furthermore, this approach involving aggregate indicator builders based on fuzzy inference systems could be, more generally, combined with fault diagnosis methods, for instance, to estimate the built-in variables necessary to qualify the vehicle behaviour, the driver's behaviour, and so forth.

The proposed real-time longitudinal velocity fuzzy estimator is integrated into a project whose aim is to determine the estimated velocity vector of the vehicle without any expensive sensor. The study of the lateral velocity estimation of a FWD car is currently being carried out.

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