STATISTICAL SIGNAL PROCESSING FOR AUTOMOTIVE SAFETY SYSTEMS

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ABSTRACT

The amount of software in general and safety systems in particular increases rapidly in the automotive industry. The trend is that functionality is decentralized, so new safety functions are distributed to common shared computer hardware, sensors and actuators using central data buses. This paper overviews recent and future safety systems, and highlights the big challenges for researchers in the signal processing area.

1. INTRODUCTION

Henry Ford revolutionized the automotive industry more than 100 years ago with his new production ideas. We are now facing another major shift in automotive production, when an increasing part of the value of the car comes from electronic systems. The introduction of more automotive safety systems plays an important role in this shift. For instance, one expert predicts that the value of software will increase from 4% in 2003, to 13% in 2010. This of course affects the engineering community in many ways. The automotive industry has always been dominated by mechanical engineers, but today we see an increasing need for engineers specialized in signal processing, automatic control, electronics, communication and computer hardware.

A key reason for this trend is the rapid development of safety systems. As the number of vehicles on our public roads increases, the requirement on safety is also increased. There has been a tremendous progress in this area over the last two decades as is evident from accident statistics. For instance, the number of fatalities in Sweden [22] suddenly started to drop around 1990. According to this report, the car fleet becomes safer for each year and the trend is that the fatality risk in a new car is reduced 5% each year. A research report by an insurance company [21], partly acknowledges on-board safety systems for this trend change, and for instance it ranks an electronic stability system (anti-skid control) as important as safety belts to prevent severe injuries on skiddy roads. The requirements on the safety systems will continue to increase in the future, motivating the continued development on improved versions of existing and new safety systems. The automotive executives share this view [39], as summarized in the conclusion “safety is a basic tenet to the industry now and will continue to be an ongoing major focus for consumers and manufacturers alike”. Further, “new technology will be as important as new models in attracting customers”.

The research community also has to contribute to this shift, and the purpose of this paper is to point out certain directions in signal processing where research is needed. The underlying theme is *sensor fusion*: to utilize existing and affordable sensors as efficiently as possible for as many purposes as possible. We point out certain more or less open problems in spectral analysis, non-uniform sampling, system identification, change detection, diagnosis and fault detection and model-based filtering and prediction to mention a few.

The outline of the paper is as follows. Section 2 overviews existing and some future control systems, where accurate information of the own and surrounding vehicles state is needed. Then, with this as a motivation, the following challenges are discussed:

Challenge I: *Wheel speed analysis*, using wheel speed as a generic multi-purpose sensor, is discussed in Section 3.

Challenge II: *Virtual sensors* for monitoring and control systems are discussed in Section 4.

Challenge III: *Navigation* as dynamic state estimation for monitoring and control systems is discussed in Section 5.

Challenge IV: *Situational awareness* by target tracking and road prediction for collision avoidance systems is discussed in Section 6.

Challenge V: *Sensor-near signal processing*, for improving and supplementing the sensor fusion, is discussed in Section 7.

Section 8 discusses various implementation aspects of a sensor fusion system, and Section 9 summarizes how sensor fusion may be structured in the future.

2. AUTOMOTIVE SAFETY SYSTEMS

In this section, we will list and briefly present some different examples of new functions or systems being developed for or already in use in modern, high-end vehicles. The idea is to highlight that a rather small number of actuators and sensors would cover all functions, and any further new function could thus often be added as a pure software module.

2.1. Safety system overview

Automotive safety systems can be grouped in many ways. The traditional way separates *active safety* (driving safety) systems that prevent accidents and *passive safety* (crash protection) systems that protect humans at an accident.

For passive safety, the signal processing opportunities are mainly in collision and roll-over detection for firing internal airbags and seat-belt pre-tensioners. Adaptive airbags for the passengers can fire at two or more levels. These systems require quite advanced signal processing and sensors mainly for classifying the passenger size and position. In the future, also external airbags and bonnet lifting for pedestrian protection systems [41, 25] may need advanced situational awareness.

2.2. Dynamic control systems

However, the main challenges lie in active safety systems. These can be grouped into *preventive systems* (including driver information and driver drowsiness monitoring), *dynamic control systems* and *collision avoidance systems*. Some functions in the latter two categories, sometimes referred to as advanced driver assistance systems (ADAS, or just DAS) are summarized in Table 1. We here distinguish longitudinal control systems mainly used when driving straight ahead, lateral systems for cornering and maneuvering situations and rate control systems.

Table 1 illustrates that the main actuators are engine torque and brakes. The regulations currently say that the steered wheels must be physically connected to the steering wheel, thus steering is not currently used as an actuator. If these regulations change, several of the lateral control functions as yaw and roll control can be improved.

Besides the primary sensors listed above, other sensor information may be included when available as tire pressure, road friction, road condition (*e.g.* gravel roads), road inclination and banking *etc.* Such information may in some cases be communicated to the driver in monitoring systems.

2.3. Sensor fusion demands

All control systems rely on accurate state information, which implies a high requirement on sensor quality. Existing control systems come with their own inertial sensor kit, and take other basic information from sensor signals available at the CAN bus. Future control systems are likely to a higher extent take their information from existing sensors, or shared sensors. As was pointed out in the previous section, the actuators are already there, and probably they will in the future all be by-wire, which means that new control functions are easily added. The same will be true with the sensors. It is only a matter of time until all intertial sensors (accelerometers and gyroscopes in three dimensions, vertical accelerometers at all wheels, *etc.*) are required by at least one sub-system. That means that any further control functions can be implemented in just software.

Here we would like to stress the following underlying statements for this survey:

1. Accurate state information is more important than advanced control algorithms (many of them are simple P(I)D controllers). That is, often it is more important *what to feedback than how to feedback.*

2. Using sensor fusion techniques, virtual sensors can be derived that compute information that would be either too costly or even impossible to measure in practice.

3. Model-based control systems are in their infancy, and future generations may include model-based filters and controllers.

The following five sections explain how this can be achieved by improved signal processing.

3. CHALLENGE I: WHEEL SPEED ANALYSIS

Without doubt, the wheel speed sensor is the potentially most informative sensor in the car. Today, the wheel speed is measured in all cars equipped with an anti-locking braking system (ABS) system on at least one but often all four wheels. Since the introduction of ABS control, wheel speed signal has found many other uses. The different potential applications presented in scientific literature and patents are discussed in this section.

3.1. Wheel speed sensors

The wheel speed sensor works as follows. A cogged wheel with N_{cog} cogs is mounted on each measured wheel. There are two ways currently used to measure the speed. The magnetic field varies dynamically as a sinusoid when the cogged wheel rotates, which can be measured by electromagnetic sensors. Both the frequency and the amplitude change with angular speed. Because of diminishing signal amplitude, low velocities cannot be measured with this principle. The so called Hall effect gives a pulse of constant magnitude for each cog, where the pulse frequency is proportional to angular speed of the wheel. For both principles, the absolute

System	Actuator: Brake	Acc.	Steering	Driver	Primary sensors: Speed	IMU	DME	Brake	Vision
Anti-locking Brake Systems (ABS)	x	–	–	–	x	–	–	x	–
Brake Assistance Systems (BAS)	x	–	–	–	–	–	–	x	–
Cruise Control	–	x	–	–	x	–	–	–	–
Adaptive Cruise Control (ACC)	–	x	–	–	x	–	x	–	–
Stop and Go	x	x	–	–	x	–	x	–	–
Anti-spin control ($v < 20$ km/h)	x	–	–	–	x	–	–	–	–
Traction control ($v > 20$ km/h)	–	x	–	–	x	–	–	–	–
Forward Collision Warning (FCW)	–	–	–	x	x	–	x	–	–
Forward Collision Mitigation (FCM)	–	–	–	–	x	–	x	–	–
Parking aid systems	–	–	–	x	–	–	x	–	x
Forward Collision Avoidance (FCA)	x	–	x	–	x	–	x	–	–
Lane Keeping Aid systems (LKA)	–	–	(x)	x	x	–	x	–	x
Lane Change Aid systems	–	–	–	x	–	–	x	–	x
Adaptive steering	–	–	x	–	x	–	–	–	–
Yaw control	x	–	–	–	x	x	–	–	–
Roll stability control	x	–	–	–	x	x	–	–	–
Roll-over detection (airbag)	–	–	–	–	x	x	–	–	–

Table 1. Advanced driver assistance systems (ADAS) grouped by longitudinal control, lateral control and rate control, respectively. Driver is here considered an actuator controlled by a haptic warning (dashboard lamp, sound, vibration). IMU means an inertial measurement unit, comprising at least one accelerometer or gyroscope. Distance measuring equipment (DME) includes radar, lidar and sonar measuring range and angle to objects. Vision includes camera and IR sensors.

angular speed (the direction of rotation is not observable) is measured in the cog domain, not the time domain. That is, angular speed is computed as

$$\omega(t_k) = \frac{2\pi}{N_{\text{cog}}(t_k - t_{k-1})}, \qquad (1)$$

where t_k denotes the time stamp delivered by the sensor each time a cog passes it. More on this particular multi-domain sampling problem is found in Section 3.3. We can for the discussion here assume that the wheel angular speed $\omega_i(t)$ is available in continuous time for each wheel i.

The wheels can also be equipped with additional sensors for strain measurements [44] or tire pressure [14], for instance.

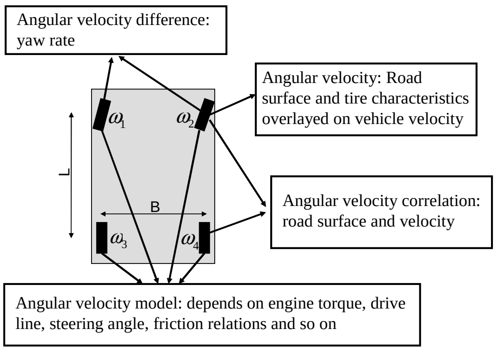


Fig. 1. Wheel speed applications.

3.2. Applications

First, the angular speeds relate to the vehicle speed at this tire by the tire radius. The speed content is a low frequency component. The tire dynamics can be modelled by three springs for torsional and radial forces in the tire rim, and the radial forces in the tire tread. Table 2 indicates the three modes. There are also wide-band noise induced from the road surface and low-frequency disturbance from the spring-damper system. Further, narrow-band disturbances as harmonics of the different rotating parts in the drive-line can sometimes be observed. Figure 2.a shows an approximation of the Fourier transform for a short batch of data with approximately constant speed. Compared to Table 2, there are no narrowband disturbances in this case, and the high frequency mode is not visible.

0-10	10-15	15-30	30-60	60-80	80-100	100–
Speed	Mode 1	Noise	Mode 2	Noise	Mode 3	Noise
Damper	Narrow-band noise components					

Table 2. Frequency spectrum for the wheel speed signal, with approximate limits in Hz.

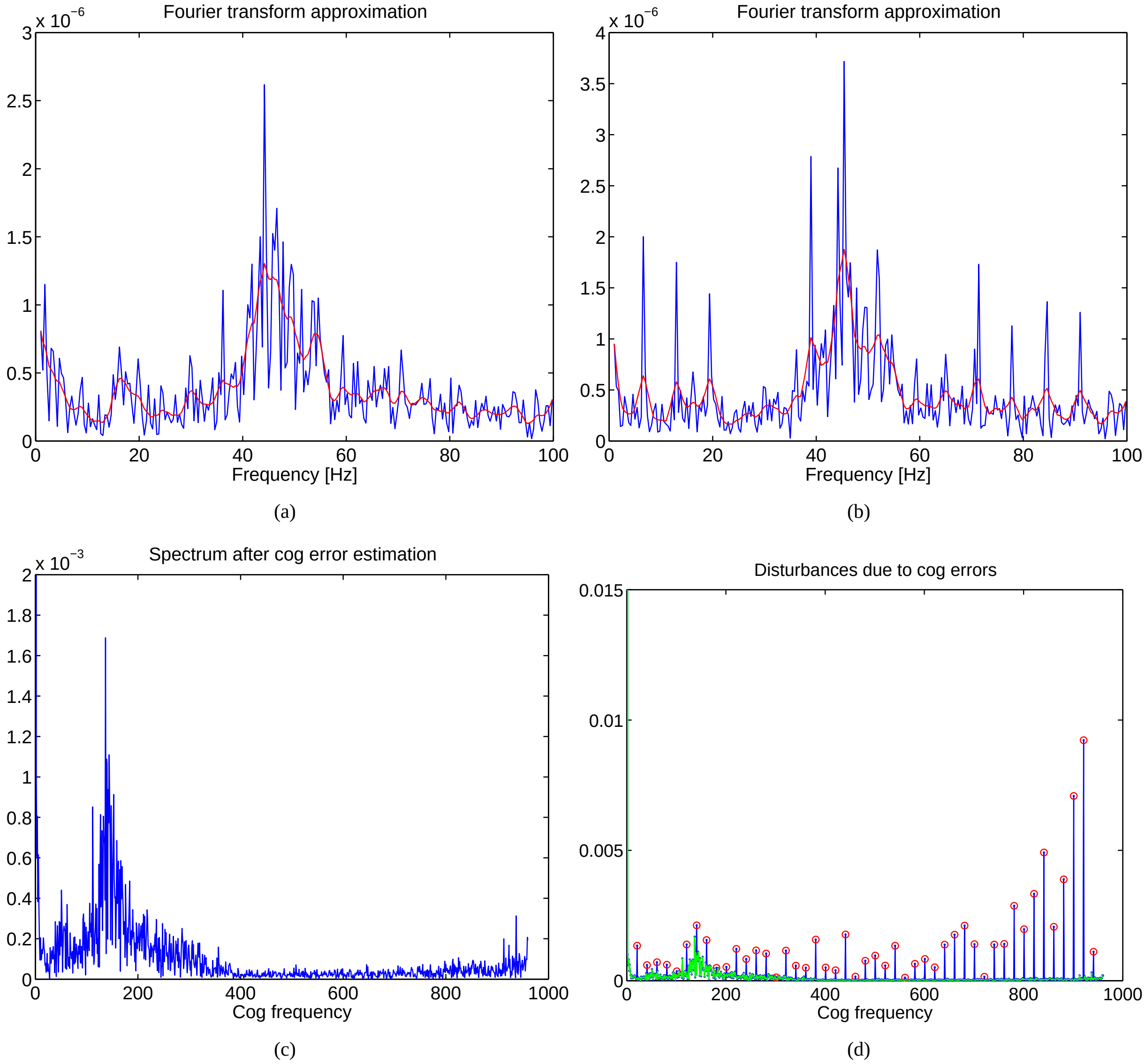


Fig. 2. Example of Fourier transform approximation (FTA) of wheel speed signal. (a) FTA of $\omega(t_k)$ after cog error correction. (b) FTA of $\omega(t_k)$ before cog error correction. (c) FTA of t_k after cog error correction. (d) FTA of t_k before cog error correction. A smoothed curve is added in (a) and (b) for peak estimation purposes.

Examples of applications of the wheel speed information found in the literature are illustrated in Figure 1 and include the following approaches:

- Temporal information (Fourier transformed velocity)

$$\Omega(f) = \int \omega(t) e^{-2\pi f t} \mathrm{d}t, \tag{2}$$

reveals, in the different frequency bands, information about tire-road friction, tire pressure, tire condition, surface texture and wheel balance information as well as wheel suspension information (spring-damper condition). A model-based alternative to the Fourier transform to analyze tire characteristics is motivated by a damper-spring model of the tire modes. Such a model corresponds to an AR(2) model, which in the frequency domain is

$$\Omega(f) = \frac{1}{(i2\pi f)^2 + 2\eta f_0 (i2\pi f) + f_0^2}, \tag{3}$$

where η is the damper constant and f_0 the eigen-frequency of the spring, respectively. This model holds only locally in the frequency band according to Table 2, so frequency selective estimation algorithms are needed.

- Spatial information (correlation of velocities) reveals absolute velocity when comparing two wheels on different axles and same side, and yaw rate information comparing two wheels on the same axle. More specifically, absolute velocity can be computed from the wheel axle distance L and time delay between disturbances passing both front and rear wheel according to the following principle:

$$\hat{\tau} = \arg\max_{\tau} \mathrm{E}\left[\omega_{\text{front}}(t)\omega_{\text{rear}}(t-\tau)\right], \tag{4a}$$

$$\hat{v} = \frac{L}{\hat{\tau}}. \tag{4b}$$

This works when the velocity is constant over the estimation time of the correlation. Open problems are how to make it velocity adaptive and to get sufficient resolution (better than the uncertainty in wheel radius, which is about a few percent).

Further, yaw rate $\dot{\psi}$, as defined in Figure 6, at the center point of the rear axle can be computed from

$$\dot{\Psi} = \frac{v_x}{R} = v_x R^{-1}, \tag{5a}$$

where the inverse curve radius should be used to avoid singularities on straight roads. From Figure 3, we have

$$\frac{v_4}{v_3} = \frac{R_4}{R_3} = \frac{R + B/2}{R - B/2}, \tag{5b}$$

leading to

$$R^{-1} = \frac{2}{B}\frac{\frac{v_3}{v_4} - 1}{\frac{v_3}{v_4} + 1} = \frac{2}{B}\frac{\frac{\omega_3}{\omega_4}\frac{r_3}{r_4} - 1}{\frac{\omega_3}{\omega_4}\frac{r_3}{r_4} + 1}. \tag{5c}$$

That is, yaw rate can for a front-wheel driven car be computed as

$$\dot{\Psi} = \frac{\omega_3 r_3 + \omega_4 r_4}{2}\frac{2}{B}\frac{\frac{\omega_3}{\omega_4}\frac{r_3}{r_4} - 1}{\frac{\omega_3}{\omega_4}\frac{r_3}{r_4} + 1}, \tag{5d}$$

provided that the wheel radii are known and that the angular speeds of the rear wheels are measured.

- Model-based approaches to friction estimation (longitudinal and lateral slip models), including handling conditions as aqua planning and rough road detector. Further, dynamic state estimation and navigation using dead-reackoning are based on wheel speeds.

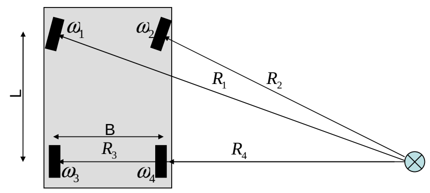


Fig. 3. Notation for the curve radius relations.

3.3. Multi-domain signal processing

As pointed out in Section 3, wheel speed sensors are perhaps the single most important sensor in a wheeled vehicle. These sensors are integrated in the ABS system, which converts raw cog time measurements to wheel speeds and communicate this refined information on a databus to dependent sub-systems. However, this pre-processing destroys information and in high-precision applications where very accurate wheel speed information is needed, more sophistacated signal processing is required. For instance, just interpolating the wheel speed in (1) without pre-processing, and then the discrete Fourier transform would give the curve in Figure 2.b. Here, the disturbance is clearly visible as narrow-band peaks. For larger batches of data, velocity variations will cause a leakage phenomenon, so the interesting information would no longer be visible. Figure 2.c shows the discrete Fourer transform of the cog time stamps t_k in (1), and with appropriate pre-processing [49, 59], Figure 2.d is obtained. These corrected time stamps can then be tranformed to wheel speeds by (1), and Figure 2.a is finally obtained.

This is a general multi-domain sampling problem. Here the sensor samples uniformly in the amplitude domain (the time for each angular change of $2\pi/N_{\text{cog}}$ is measured), while all consequent algorithms are based on uniform sampling in the time domain. Note that there is a similar sensor in the engine control system, where similar algorithms can be utilized.

4. CHALLENGE II: VIRTUAL SENSORS

A virtual sensor [30] is here defined as a physical quantity not directly measured, which is computed from existing sensors. The reason could be to avoid costly sensors, as in the tire pressure monitoring system in Section 4.2, or to compute abstract quantities as tire road friction as in Section 4.1, where practically feasible sensors do not exist.

4.1. Road friction monitoring

A friction information system would be central for all dynamic control systems in Table 1, and would provide valuable information for the driver. The literature on this subject is quite rich, see the survey [46], and a multitude of approaches have been investigated:

- Slip based approaches, utilizing the noticable change in wheel slip (both lateral and longitudinal) with tire road friction [27].
- Spectral analysis of wheel speeds, as discussed in Section 3.
- Audio-based classification based on microphones 'listening' to each tire [60].
- Vision-based classification based on surface texture and reflection properties [19].
- Behavioural approaches analysing the driver behaviour [19], assuming the driver is aware of the friction and adapts his driving style. This is of course not an approach for monitoring, but can be used for initializing ABS control for instance.
- Sensor-based approaches where the sensors are mounted in the tires' tread for measuring stress [19].

Despite these efforts, no friction monitoring system exists on the market. Friction is a complicated physical phenomenon, and the variety of tire models and possible combination of makes and wear has delayed the introduction of large scale cheap commerical friction estimators substantially. Accurate and robust friction estimation may require multiple approaches with an over-all information fusion. Basically, all the approaches listed above can be used to obtain a more robust estimate.

Model-based slip estimation approaches still contain several challenging open signal processing problem, and will be described in some detail in the following.

4.1.1. Longitudinal slip

The longitudinal dynamics of a car depends non-linearly on the friction via the so called wheel slip, defined as

$$s = \frac{\omega r - v_x}{v_x} = \frac{\omega r}{v_x} - 1 \tag{6}$$

The obtained friction force normalized by the normal force on a certain wheel,

$$\mu = \frac{F_x}{N_z}, \tag{7}$$

is given by a non-linear function known as the slip curve. This relation is illustrated in Figure 4.a for some different surfaces for positive friction forces (wheel spin), and a similar relation holds for braking. For friction estimation and control purposes, the slip curve should be considered as time-varying, and adaptive estimation methods are desired.

4.1.2. Slip models

The so called "*magic tire formula*" [7] is the best known and most cited parametric model of the slip curve. It is defined as

$$\mu(s) = D\sin(C\tan^{-1}(B((1-E)s + \frac{E}{B}\tan^{-1}(Bs)))). \tag{8}$$

This model is widely accepted for its flexibility, and used for simulation and curve fitting to test bench data. A suitable set of initial values is $B = 14$, $C = 1.3$, $D = \mu_{max}$ and $E = -0.2$. The initial slope is given by $BCDE$ and to affect s_{max} one can tune B, C.

Many other alternative slip functions have been suggested [32, 61, 42, 3]. For instance, the rational function $\mu = ks/(as^2 + bs + 1)$ is suggested in [36, 37] for estimation during ABS braking. A theoretical model for friction, aimed for control purposes, is developed in [16] based on fundamental friction relations as described in for instance [6]. The model was later applied to slip curves in [17, 15]. The dynamic μ–s model (compared to the static one in Figure 4) they propose is

$$\dot{z} = v_x - \frac{\sigma_0|sv_x|}{g(sv_x)}z, \tag{9}$$

$$F_x = (\sigma_0 z + \sigma_1\dot{z} + \sigma_2 v_x)F_z, \tag{10}$$

$$g(sv_x) = \mu_C + (\mu - \mu_C)e^{-|sv_x/v_s|^{0.5}} \tag{11}$$

Here z is the state in the model and σ_i, s_C, v_s are parameters. They refer to the original model (which has a power 2 instead of 0.5 above) as the *LuGre* model.

4.1.3. *Adaptive estimation of slip models*

Some problems associated with these models are that the feasability region in the parameter space is hard to define, the parameters are not easily interpreted in the terms of initial slope, maximum friction force, stationary friction ($s \to \infty$) and the parameters in the magic tire formula have no physical meaning. This together makes the models less suitable for adaptive filtering, and research for better structures is needed.

Figure 4.b shows (s, μ) measurements from a test drive on an area with a skid pad that is reached at time 170-210. At the skid pad, a braking and spinning maneuver are performed, and adaptively estimated friction curves to both regions (skid and asphalt) are depicted in the lower plot. The fit on asphalt during low slip is quite good, but on the skid pad the fit is poor and one can imagine different friction curves in different regions. This illustrates that friction is a highly dynamic phenomenon, where a good fit over time cannot be reached even under quite controlled external conditions. That means, that reproducible experiments with high accuracy cannot be obtained usually.

For friction monitoring and warning to the driver, the conclusion from such experiments is that the scale must be quite course, perhaps only two levels indicating good or bad friction ($\mu_{max} \gtrless 0.4$ for instance). One approach to monitor friction that works also during normal driving, is to adaptively estimate the initial slope of the friction curve in Figure 4.a, which is a straight line during normal driving when $\mu < 0.1$.

4.1.4. *Estimation on longitudinal slip slope*

The initial slope is in tire literature [6] referred to longitudinal stiffness, and is considered a tire characteristic (small slope for soft tires like M+S). However, as demonstrated in [18], the slope changes slightly but significantly for different surfaces, as illustrated in Figure 5.a. This fact was used in [27, 28] for an adaptive filter based on the linear regression model

$$s(t) = \bar{k}(t)\mu(t) + \delta(t) + e(t), \qquad (12)$$

where $\bar{k}(t)$ is the inverse initial slope, $\delta(t)$ an offset and $e(t)$ noise. The offset has to be estimated. Though being a valid model easily reproducible in field tests, there are several challenges in signal processing as the contradictory requirement of fast and accurate tracking of friction, further under very poor signal to noise ratio. The recursive least squares scheme is applied to the data in Figure 5.a and the result is shown in Figure 5.b for one slow and one fast tuning. None is acceptible, so non-linear methods based on change detection are needed. Another challenge is how to handle varying excitation conditions, since $\mu(t)$ is almost constant during cruising and the parameters $\bar{k}$ and δ are not identifiable.

It has also been suggested to extend (12) with a dynamical model of the drive-line and an observer for estimating $\mu(t)$, see [50, 66].

4.1.5. *Lateral slip*

To support the ideas presented above based on the longitudinal slip, the lateral slip can be used as well. The lateral slip α_f is defined in Figure 6, and can be computed from lateral dynamics if the steering wheel angle δ_w and yaw rate $\dot{\psi}$ are measured. The relation between lateral force and side slip angle follows the same principal non-linear relation as the longitudinal friction curve in Figure 4.a. That is, the same type of algorithms as discussed above can be applied. Though the dynamics is somewhat more complicated, the excitation might be better than, or a good complement to, the excitation in lateral dynamics. One idea to estimate sideslip is to include satellite navigation in the sensor fusion [9].

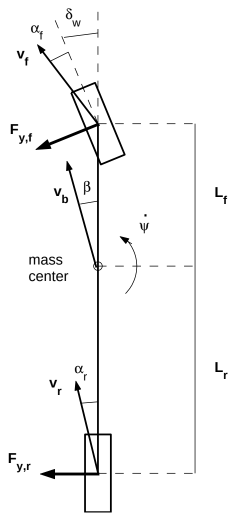
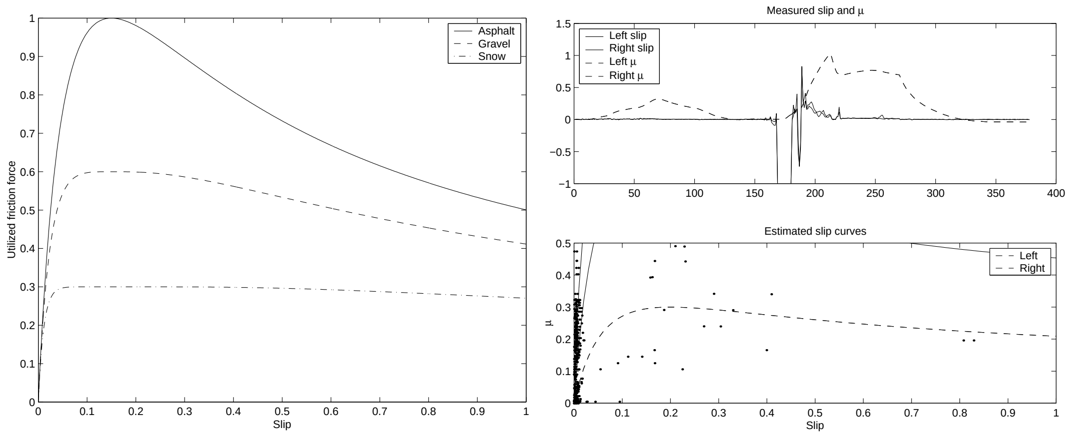


Fig. 6. Notation for the lateral dynamics.

4.2. Tire pressure monitoring systems (TPMS)

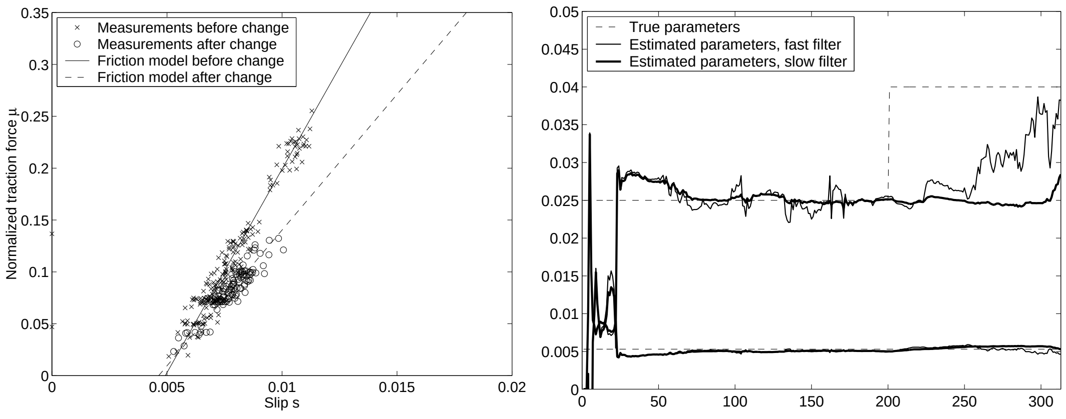
The following quote from the NHTSA press release from April 7, 2005, indicates the importance of development of reliable and affordable systems for tire pressure monitoring:

> All passenger cars will have tire pressure monitoring systems beginning with the 2006 model year according to a new motor vehicle safety standard by the National Highway Traffic Safety Administration (NHTSA). The regulation will require that manufacturers install a system that



(a) (b)

Fig. 4. (a) Friction relation between wheel slip (6) and normalized traction force (7). (b) Measured slip data on a track with skid pad, where braking and spinning are performed, and a parametrized slip curve is adaptively estimated.



(a) (b)

Fig. 5. (a) Measured traction force versus slip for good and bad friction, together with straight line fits to each region. (b) Adaptively estimated inverse slope of the friction curve for a fast and one slow recursive least squares filters.

> can detect when one or more of the vehicle's tires are 25 percent or more below the recommended inflation pressure. Phase-in of the new regulation will begin Sept. 1, 2005. All new 4-wheeled vehicles weighing 10,000 pounds or less must be equipped with the monitoring system by the 2008 model year.

Further,

> NHTSA estimates that about 120 lives a year will be saved when all new vehicles are equipped with the tire pressure monitoring systems. In addition, consumers should see improved fuel economy and increased tire life.

See `http://www.nhtsa.dot.gov/cars/rules/rulings` for more details. The user interface is suggested to be as in Figure 7.

Today, most TPMS are sensor based [14, 2], using a pressure, temperature and possibly acceleration sensor in each wheel, each sensor kit equipped with a radio transmitter and battery. This is perhaps more of a sensor technology challenge.

However, there are indirect systems as well utilizing the wheel speeds at a much lower cost. The basic idea, found in implementations on the market today, is to monitor a residual of the form

$$e(t) = \frac{\omega_1(t)\omega_4(t)}{\omega_2(t)\omega_3(t)} - 1 \tag{13a}$$

$$= \frac{v_1(t)v_4(t)}{v_2(t)v_3(t)} \frac{r_2(t)r_3(t)}{r_1(t)r_4(t)} \frac{1+s_1(t)}{1+s_2(t)} - 1, \tag{13b}$$

where the numbering of angular speeds ω_i, wheel speed v_i and wheel radius r_i is defined in Figure 1. A front-wheel driven vehicle is assumed, and the slip model (6) is used in the second equality. The residual $e(t)$ is non-zero if at least one of the following occurs:

- The slips s_1 and s_2 are different on the left and right side (split μ situation),
- The wheel speeds do not match each other. Note from Figure 3 that $v_1/v_2 = v_3/v_4$ if a circular path is followed.
- One of the wheel radii differs from the other ones.

It is the last property that can be used for TPMS. It is clear from its construction that four wheel pressure decrease (so called diffusion) cannot be detected from $e(t)$, and also simultaneous decreases on one axle or one side might be unobservable. More advance methods make use of sensor fusion on different scales. First, wheel speed analysis as described in Section 3 may indicate tire pressure information [49, 67, 62]. Second, model-based sensor fusion can improve the estimation of relative tire radii substantially. High-level fusion of different principles may in the end enable a TPMS that satisfies the NHTSA rules.

Fig. 7. The TPMS warning symbol.

5. CHALLENGE III: DYNAMIC STATE ESTIMATION

The dynamic control systems in Table 1 need accurate state information about the vehicle's position and orientation and their time derivatives. This is in general a model based filtering problem where the (extended) Kalman filter applies, where a partial vehicle model is used to improve sensor measurements and for diagnosis. We will here describe two non-standard problems.

Examples of application include [29]

- Offset-free velocity and acceleration (longitudinal dynamics) for cruise control and collision mitigation [64].
- Offset-free yaw rate and drift-free yaw angle (lateral dynamics) that can be used for ESP, lane keeping aid and navigation.
- Offset-free roll angle estimation (roll dynamics) for use with motorcycles (ABS, anti-spin, headlight control) or offset-free roll rate for vehicles (air bag curtains and roll-over detection).
- Positioning support and backup for satellite based positioning as the Global Positioning System (GPS) [23]. This includes improved dead-reckoning with small drift.

5.1. Sensor fusion for offset estimation

One general idea of how to estimate sensor offsets using sensor fusion is as follows. Suppose there are two measurements $y_i(t)$ of the same variable x, where each measurement has an offset b_i:

$$y_1(t) = x(t) + c_1(t)b_1 \tag{14a}$$

$$y_2(t) = x(t) + c_2(t)b_2. \tag{14b}$$

Here the offset scaling $c_i(t)$ is a known function of time. These two equations have three unknowns and is unsolvable, so there is no way to eliminate the offsets directly without more information.

When two pairs of measurements, $y_1(1)$, $y_2(1)$, $y_1(2)$, $y_2(2)$, become available, we get two more equations and only one more unknown. That is, we have four unknowns and four equations and we can solve for the offsets *and* the variables $x(1), x(2)$. The only condition is that there is no linear dependency in data, which here means that

$$\frac{c_1(1)}{c_1(2)} \neq \frac{c_2(1)}{c_2(2)}.$$

If this is not satisfied, one can just wait until two equations that are not linearly dependent are obtained. For instance, if c_1 is constant and $c_2(t) = v_x(t)$ is the velocity, the equation system is solvable as soon as the velocity changes. This can be defined offset *observability* or *identifiability*.

This is the basic idea, and there are two extensions to make the solution more realistic.

Extension 1: Assume there are measurement noises added to the observations. Then we can collect many observations and get an overdetermined equation system and compute the least squares solution. In this way, the solution will be more robust to the measurement noise. A perfect sensor fusion match is obtained if one sensor is good in the high-frequency region and the other one in the low-frequency region.

Extension 2: The variable x is a correlated sequence that cannot change arbitrarily fast between two observations. This kind of a priori knowledge is difficult to put down into algebraic equations, but is easily handled by filter theory (Kalman filter). The implication is that the accuracy in the estimate of $x(t)$ might be even better than using the average of two *offset-free* sensors, when only spatial information is used.

To concretize, let $y_1(t)$ be the integrated acceleration of measurements from a longitudinal accelerometer with a slowly time-varying offset, and $y_2(t)$ be the velocity computed from the wheel speed sensor using a nominal wheel radius r_{nom} with offset Δr. To simplify, assume the accelerometer is placed on top of the wheel, so the two measured velocities are defined at the same position. We then have

$$\begin{aligned} y_1(t) =& \sum_{k=0}^{t} a(k) = v_x(t) - v_x(0) + bt + e_1(t), \\ y_2(t) =& \omega(t) r_{nom} = v_x(t) + \omega(t)\Delta r + e_2(t). \end{aligned}$$

Since the scalings $c_1(t) = 1$ and $c_1(t) = \omega(t)$ are linearly independent if the velocity is not constant, the two offsets can in principle be resolved.

5.2. Positioning

Navigation systems as well as some future ADAS need accurate and robust position information. Usually, this is provided by the GPS but infrastructure road beacons can be used as well [55]. So called map matching puts the GPS position on the nearest road found in a digital map, and a yaw rate gyro is used to improve orientation estimation during cornering. Further, gyro and speedometer based dead-reckoning is used temporarily when GPS is not available [1, 11]

Positioning accuracy is today limited by the digital maps, which are usually based on digitized paper maps. It has been proposed to use sensor fusion ideas to merge (differential) GPS with on-board sensors so a car can be used as a measuring probe to automatically generate high-accuracy street maps [53, 65]. In the sequel, we assume that the street map is given.

A sensor fusion approach to positioning can be based on the motion model

$$\begin{aligned} x(t+1) =& x(t) + Tv(t)\cos(\psi(t)) + w_x(t), && \text{(15a)} \\ y(t+1) =& y(t) + Tv(t)\sin(\psi(t)) + w_y(t), && \text{(15b)} \\ \psi(t+1) =& \psi_t + T\dot{\psi}(t) + w_\psi(t), && \text{(15c)} \end{aligned}$$

where the state vector $\mathbf{x} = (x, y, \psi)$ contains position and orientation of the vehicle, and $w(t)$ denote process noise. Speed $v(t)$ and yaw rate $\dot{\psi}(t)$ are considered as inputs. The measurement relation may include GPS, wheel-speed computed yaw rate (5d), but also implicit information such as the constraint that the vehicle is most likely located on a road. Such mixture of classical sensor information with database implied constraints are not easily incorporated in the classical Kalman filter framework. However, the particle filter [52] provides a tool for solving the filtering problem [23]. Such map based positioning can be used as a GPS replacement or as a complement when GPS is not operating properly (tunnels, urban areas or forrests suffering from multipath). Figure 8 illustrates one real-time product of this kind.

6. CHALLENGE IV: SITUATIONAL AWARENESS

In particular collision avoidance systems and adaptive cruise controllers need advanced situational awareness, and short time prediction of the road and other vehicles' motion is crucial for safety related systems. Pre-crash systems, such as belt pre-tensioners and pedestrain protection systems, need accurate predictions and an estimate of the type of object of an imminient collision. Further, future engine control systems may need a road prediction for optimizing fuel economy and for automatic gear shifting.

The main sensors needed for situational awareness are one or a combination of radar [45], laser scanner [47, 25], lidar ([58] describes a 3D version), IR (including so called thermopiles [41]) and vision [51].

We split the situational awareness into the following subproblems:

Fig. 8. Positioning without GPS, using the particle filter based on wheel speed measurements and road map only, here implemented in a handheld computer.

- Classical *target tracking* problems, including *Object recognition* and the data association problem, which are more or less similar problems to what is studied in the area of air traffic control [8].
- *Tracking and prediction of ego-motion* (estimation of host vehicle state).
- *Road geometry tracking and prediction*.
- *Decision algorithms* for warning and intervention systems.

Most publications in this field are concerned with target tracking and object recognition, describing sensor fusion with a subset of the sensors listed above: Sensor fusion of laser scanner and vision in the European Union project PROTECTOR is described in [35], while [26] also includes radar for pedestrian protection within the same project. Sensor fusion with focus on pedestrians is also treated in [43]. A Bayesian framework for sensor fusion is described in [12, 13], within the EU project CARSENSE. In the same project, [40] focuses on low speed situational awareness. Fusion of radar and IR is described in [54] and [48] fuses laser scanner and vision. Sensor fusion with focus on lateral tracking is described in [38] based on GPS, vision and radar and in [5, 4] based on vision and radar.

An ACC system based on inter-vehicle communication is described in [63]. Sensor requirements for a stop and go ACC system is discussed in [31, 24, 25].

A straightforward decentralized implementation of filters for situational awareness might look like the upper structure in Figure 9. The filters all need motion models for the road geometry, the ego-motion, the motion of tracked vehicles (often simpler than for ego-motion), and even a separate model for decision support.

However, road geometry and vehicle movements are highly correlated, and further dependent on the type of vehicle (motorcycles have fast dynamics, bikes move slowly and close to the road side, *etc.*). More specifically, a lateral movement of tracked vehicles can be due to either a lane change or road bend, but a yaw change in the host vehicle gives quite similar sensor signals from the radar, lidar or vision sensor. Further, a displacement in two consequtive video frames of the radar bearing measurement from a stationary object may be used as a virtual yaw velocity sensor. See the left plot in Figure 13 for and illustration.

This motivates a centralized filtering approach according to the centralized filter in Figure 9. Here, the state vectors of the tracked vehicles and the road are merged into one state vector. In this way, movements of the tracked vehicles influence the road geometry estimate and *vice versa*.

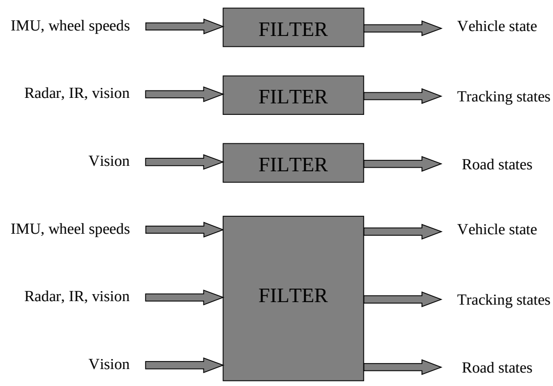


Fig. 9. Decentralized versus centralized filtering.

6.1. A fusion model for filtering

The idea in centralized filtering is to merge all states in the models for road geometry, ego-motion and tracked vehicles into one state vector, cross-utilizing all measurements. One such model was developed independently in [20] and [38]. Because of its potential role as sensor fusion glue between sensors and model-based filters, it will be outlined in some detail below.

Road geometry can be approximated with constant jerk, leading to a linear relation for inverse curve radius $R^{-1} = c_0 + c_1 x$. According to (5a), the yaw rate then becomes linear in time when the speed is constant corresponding to smooth steering wheel maneuvers.

The coordinates x and y denote the position in the curved coordinate system, which is attached to the road according to Fig. 10. In these coordinates, the motion model for the tracked vehicles can be greatly simplified. For example, it allows us to use the equation $\dot{y}^i = 0$, which simply means that it is assumed that the tracked vehicle number i will follow its own lane. In the longitudinal direction we will use

$\ddot{x}^i = -a\cos\Psi_{rel}$, where a is the measured acceleration of the host vehicle and Ψ_{rel} is the angle between the host vehicle and the lane. Hence, we have the following motion model:

$$\dot{x}^i = v^i, \tag{16a}$$
$$\dot{v}^i = -a\cos\Psi_{rel}, \tag{16b}$$
$$\dot{y}^i = 0, \tag{16c}$$

where v^i is the longitudinal velocity of object i, *i.e.*, the time derivative of x^i. Furthermore, Ψ_{abs} is the angle between the host vehicle and some fix reference. We can obtain a relationship between the Ψ_{rel} and Ψ_{abs} by differentiating Ψ_{rel} w.r.t. time,

$$\Psi_{rel} = \Psi_{abs} + \Psi_{lane} \quad \Rightarrow \tag{17a}$$
$$\dot{\Psi}_{rel} = \dot{\Psi}_{abs} + \dot{\Psi}_{lane} = \dot{\Psi}_{abs} + \frac{v}{R} = \dot{\Psi}_{abs} + c_0 v, \tag{17b}$$

where r is the current road radius, v the velocity and Ψ_{lane} denotes the angle between the lane and some fix reference. $\dot{\Psi}_{abs}$ can typically be measured with a yaw rate sensor. We also have

$$\dot{y}_{\mathit{off}} = \sin(\Psi_{rel})v \approx \Psi_{rel} v. \tag{18}$$

Using $\dot{W} = 0$ and $\dot{c}_1 = 0$ continuous-time motion equations for the host vehicle states and the road states can be written

$$\dot{W} = 0, \tag{19a}$$
$$\dot{y}_{\mathit{off}} = v\Psi_{rel}, \tag{19b}$$
$$\dot{\Psi}_{rel} = vc_0 + \dot{\Psi}_{abs}, \tag{19c}$$
$$\dot{c}_0 = vc_1, \tag{19d}$$
$$\dot{c}_1 = 0. \tag{19e}$$

A further extension of this model to three-dimensional road models is possible by including a road curvature R_y along the lateral y-axis. Roads are constructed under constraints on the visible horizon with a parabolic design rule $z = x^2/(2R_y)$. A linear model is plausible for the variation in R_y^{-1} here as well, similar to the for R_z around the z-axis. Such a 3D model can be used by ACC systems for fuel economy and collision avoidance system by warning for possible vehicles 'behind the hill'.

6.2. Decision evaluation

For illustration of the main concepts in decision evaluation, consider the so called *time to collision*

$$T_{\text{TTC}} = \frac{r(t)}{v(t)} \tag{20}$$

as a risk metric. Here r denotes the range to the object and v the relative speed. The following cases need to be considered.

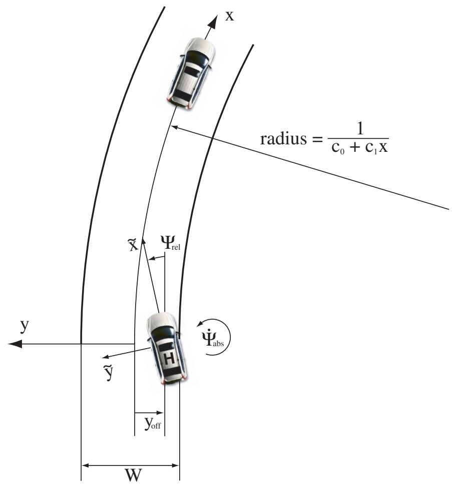


Fig. 10. The coordinate systems used in deriving the dynamic motion model. Here, (x, y) denotes the position in a curved coordinate system, which is attached to and follows the road. Furthermore, $(\tilde{x}, \tilde{y})$ denotes the position in a coordinate system, which is attached to the moving host vehicle.

- a^0: No action if $T_1 < T_{\text{TTC}} < T_0 = \infty$.
- a^1: Warning if $T_2 < T_{\text{TTC}} < T_1$. Here any driver can easily avoid collision, but a prompt action is needed.
- a^2: Avoidance maneuver is issued if $T_3 < T_{\text{TTC}} < T_2$. Here only a very alert and skilled driver can avoid collision.
- a^3: Mitigation actions are activated if $0 = T_4 < T_{\text{TTC}} < T_3$. The collision is unavoidable regardless of steering/braking manuevers.

One problem here is that p and v are estimated from sensor measurements, and thus are uncertain. From a Bayesian viewpoint, T_{TTC} can be considered a stochastic variable, and the action taken becomes random. There is thus a need for designing decision algorithms based on estimated state variables.

The question of how to interface filters providing uncertain state information with decision algorithms based on perfect state knowledge is illustrated in Figure 12. A general approach is based on Monte Carlo simulations. First, take a number N of samples $(r^i(t), v^i(t))$ from *a posteriori* distribution $p(r(t), v(t)|y(0), \ldots, y(t))$ given all past sensor observations. Then, compute the confidence in each action as

$$p^k = \mathrm{Prob}(a^k(t)) = \frac{1}{N}\sum_i I\left(T_{k+1} < \frac{r^i(t)}{v^i(t)} < T_i\right), \tag{21}$$

where $I(\cdot)$ is the binary indicator function.

This Monte Carlo approach can be generalized to supervise more complex decision criteria for collision avoidance applications, see the survey in [34], as outlined in Figure 12. As a further illustration, Figure 11 shows a snapshot from a test case where a critical situation has arised after a lateral drift over the lane borders of the host vehicle. The own state is known with some uncertainty, the position of the stationary threat is tracked with some uncertainty, and it is unknown what the driver intends to do. What is the consequence of a braking or steering maneuver? If all state vectors were perfectly known, a prediction would reveal if and when a collision would occur.

Fig. 11. What is the risk for collision, and how to evaluate braking and steering control decisions?

7. CHALLENGE V: SENSOR-NEAR SIGNAL PROCESSING

7.1. Radar and lidar as a vision system

A radar system transmits a pulse and thresholds the response to get a range detection at each scanned bearing. The idea of *"track before detect"* in the target tracking literature [10, 56], is to measure the received signal energy in each range-bearing(-doppler) cell of the radar. In this way, a 2D (3D) image is obtained from the received waveform, as illustrated in the right plot in Figure 13. This can be used for estimating the spatial size of the object and its reflectance, which further is very useful for object classification. One of the few automotive publications on this approach [41] introduces the term "occupancy grid" thermopile sensors.

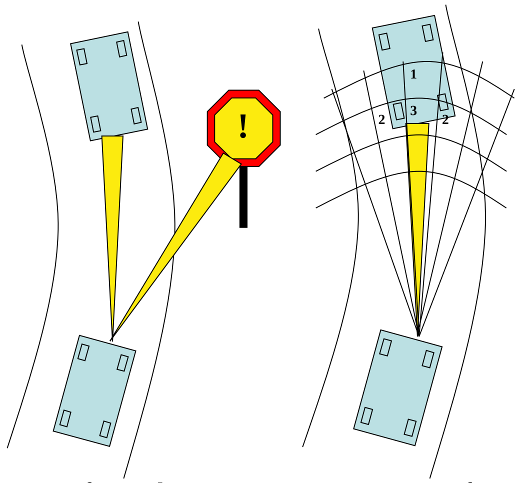


Fig. 13. Left: Radar as a sensor. Responses from moving objects are used for tracking and from stationary objects they can be used as inertial measurements. Right: The "track before detect" concept, where the received radar energy in each range-bearing cell is measured, rather than thresholded (detected).

7.2. Vision as a sensor

One basic output from image processing is a list of features. In signal processing terms, each feature is an *implicit nonlinear measurement* of the kind:

$$h(\mathbf{z}^i(t), \mathbf{x}(t), \mathbf{f}^i) = 0, \quad i \in I(t) \tag{22}$$

Here $\mathbf{z}^i(t)$ is the image coordinates of feature i belonging to the set $I(t)$ of features visible at time t, $\mathbf{f}^i$ denotes the corresponding feature position i (usually unknown), and $\mathbf{x}(t)$ is the camera state at time t. The camera position $\mathbf{c}(t)$ and orientation $\mathbf{q}$ (quaternion or any other angle representation) at time t are included in the state vector $\mathbf{x}(t)$.

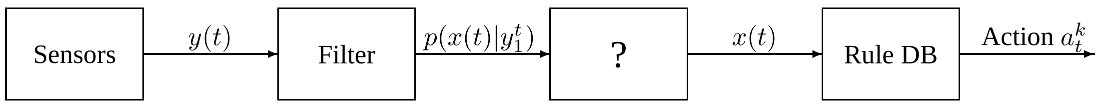
7.2.1. Real-time feature extraction

There is a need for developing real-time versions of low-level primitives for feature extraction the image processing area. One example of such an efficient algorithm is the Harris detector [33], which is based on local maxima and minima in the function $f(\mathbf{z})$ defined as

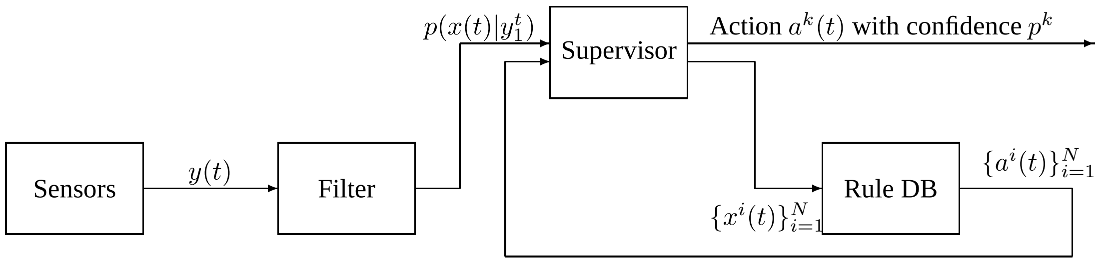
$$H(\mathbf{z}) = \hat{\nabla}(\mathbf{z})\hat{\nabla}^T(\mathbf{z}), \tag{23a}$$

$$f(\mathbf{z}) = \det(H) - 0.04\,\mathrm{trace}(H). \tag{23b}$$

Here, $\hat{\nabla}\mathbf{z}$ is a numerical approximation of the gradient in the image, and $H(\mathbf{z})$ becomes an approximation of the Hessian. The idea is that $f(\mathbf{z})$ is small at points where the grey scale in the image is locally constant, it is negative when the grey scale is monotonously increasing in one direction, and positive when there are two or more local gradients ($H(\mathbf{z})$ is full



(a) The problem: how to interface uncertain state estimates with deterministic decision making? Should $x(t)$ be taken as the minimum variance estimate?



(b) One solution: a supervisory algorithm that assesses confidence in action decisions using Monte Carlo integration by sampling from $p(x(t)|y_1^t)$, where y_1^t denotes all past measurements.

Fig. 12. Collision avoidance based on uncertain information.

rank) in the image. That is, $f(\mathbf{z})$ is a large positive number at corners and a large negative number at edges.

The plus signs in Figure 14 are computed using large values in the Harris detector. Suppose the association problem can be resolved, so each detection is associated to one tracked object or to the stationary background. The detection on tracked vehicles can be used for firstly tracking and secondly for getting a rough feeling for the size of each moving object on which object recognition can be based on. The detections from stationary objects can be used for virtual yaw, roll and pitch sensors. A preview of some mathematical models needed for this is given in the next sections.

7.2.2. Vision as an inertial sensor

The feature and camera position can be thought of in a fixed coordinate system, where one choice of state vector is

$$\mathbf{x} = \begin{pmatrix} \mathbf{c} \\ \dot{\mathbf{c}} \\ \mathbf{q} \end{pmatrix}. \tag{24}$$

The global position of the features is usually not known, unless we presume recognizable beacons or road signs with database position support. However, the *feature displacement* between two consequtive frames contains information of the host's relative motion. The relation can be expressed as [57]

$$\begin{aligned}&[(\dot{\mathbf{z}}_{x,\mathrm{dis}} - \dot{\mathbf{z}}_{x,R})f,\ (\dot{\mathbf{z}}_{y,\mathrm{dis}} - \dot{\mathbf{z}}_{y,R})f,\\ &(\dot{\mathbf{z}}_{y,\mathrm{dis}} - \dot{\mathbf{z}}_{y,R})\mathbf{z}_x - (\dot{\mathbf{z}}_{x,\mathrm{dis}} - \dot{\mathbf{z}}_{x,R})\mathbf{z}_y]\,\dot{\mathbf{c}}(t) = 0.\end{aligned} \tag{25}$$

where

$$\begin{aligned}\dot{\mathbf{z}}_{x,\mathrm{dis}} &= \frac{z_x(t) - z_x(t-1)}{T_s},\\ \dot{\mathbf{z}}_{y,\mathrm{dis}} &= \frac{z_y(t) - z_y(t-1)}{T_s},\\ \dot{\mathbf{z}}_{x,R} &= f(1 + \frac{z_x^2(t)}{f^2})\omega_x - \frac{z_x(t)z_y(t)}{f}\omega_y + z_x(t)\omega_z,\\ \dot{\mathbf{z}}_{y,R} &= \frac{z_x(t)z_y(t)}{f}\omega_x - f(1 + \frac{z_x(t)^2}{f^2})\omega_y + z_y(t)\omega_z.\end{aligned}$$

That is, $\dot{\mathbf{z}}_{x,\mathrm{dis}}$ is the displacement of a feature in the x-direction in the image, $\dot{\mathbf{z}}_{x,R}$ is the rotation of the feature affecting the image projection along the x coordinate, and similarly for the y coordinate.

The relation (25) is linear in the velocity $\dot{\mathbf{c}}$ and nonlinear in the rotation $\mathbf{q}$, and its linearized version might be used in an extended Kalman filter to gain information of speed and rotation (not absolute position).

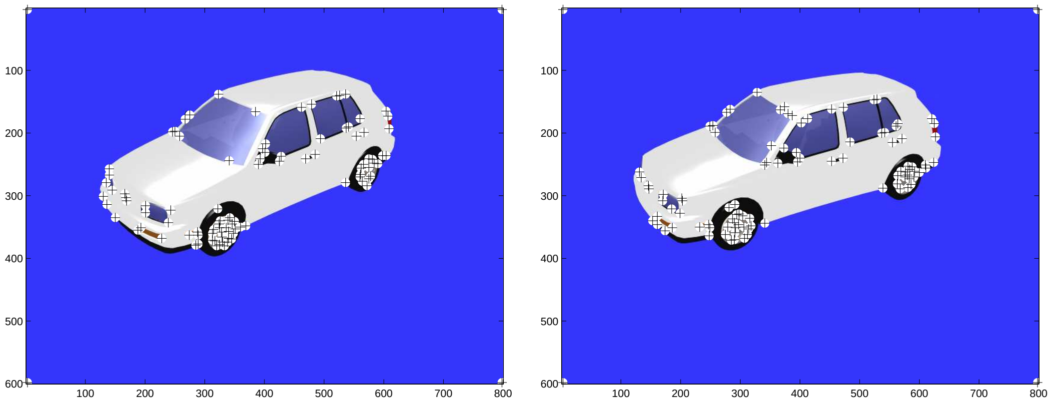
7.2.3. Vision as a tracking sensor

For target tracking, the state vector (24) denotes relative coordinates between the tracked vehicle and the host. Each feature on the tracked vehicle can be considered as a 3D correspondance, with

$$\left[-fI_2,\ \tilde{\mathbf{z}}^i(t)\right] R(\tilde{\mathbf{q}})\tilde{\mathbf{c}}^i(t) = 0 \tag{26}$$

where $\tilde{\mathbf{z}}^i(t)$ denotes the image coordinates for vehicle i at time t, $\tilde{\mathbf{c}}$ is the relative 3D coordinates, $\tilde{\mathbf{q}}$ is the relative orientation and $R(\tilde{\mathbf{q}})$ denotes an relative orientation matrix.

We have to bear in mind that such implicit relations can be re-parametrized. The ones chosen here are chosen to be as linear as possible in a certain sense. In general, the more linear relation, the easier expressions and the more accurate EKF.



(a) (b)

Fig. 14. Two images from the video stream used to obtain the vision measurements. Features using the Harris detector in (23) have been indicated in the images. The camera has been rotated 10 degrees from the upper to the lower image, and the feature displacements can be used for tracking and navigation.

8. SENSOR FUSION IMPLEMENTATION

8.1. Trends in software architecture

The current software architecture in cars use local computation nodes for each function, and often the function supplier also provides dedicated sensors. This will in the end be quite an inefficient structure, with a lot of redundant sensors and processors. Today, both navigation guidance systems and dynamic control systems come with yaw rate gyros for instance. There can be more than ten micro-processors in a modern car, ranging from important computational nodes in the ABS and engine control systems, to mostly disabled nodes in the audio, keyless entry and airbag systems.

There is a trend that the OEM's want to take back the initiative for system design from the tier one suppliers. This requires an open architecture, with a clear interface between sensors, actuators and software applications to the micro-processor the OEM provides. Figure 15 illustrates a natural development. Here, also future short range communication functionality is indicated, with the idea to 'exchange state vectors' with each other, and communicate intentions and warnings. Such communication protocols are today standardized for commercial aircraft (AIS) and surface (ADS) traffic, respectively. The next section summarizes two such recent trends, followed by a section on trends in local communication protocols.

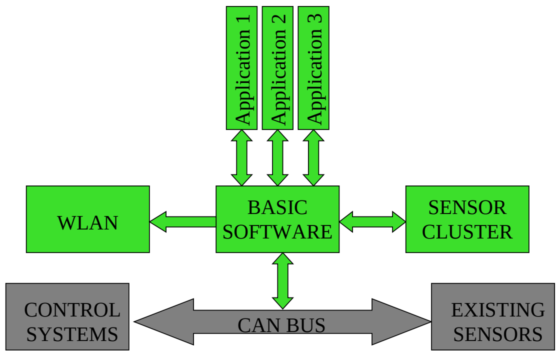


Fig. 15. Sensor cluster

8.2. Architecture standardization

The German-French initiative OSEK-VDX `http://www.osek-vdx.org`, started in 1993, has proposed an open standard for systems architecture. The project aims at facilitating efficient design, integration, and testing operating system, communication protocols and network management. This is today considered an industry standard. However, there have been competing proposals from both American and Japanese groups.

The Automotive Open System Architecture (AUTOSAR) `http://www.autosar.org` initiative was launched in 2002. AUTOSAR aims at addressing important questions like how to handle increased complexity, scalability, availability, and product changes, software updates *etc.* during a vehicle's lifetime. One key feature of AUTOSAR is modularity: definition of a modular software architecture, specific problems associated with hardware-dependent and hardware-independent software *etc.* Another key feature is flexibility, which *e.g.* means integration of software from different suppliers in one node or electronic control unit, transportability of software to allow resource allocation optimizations on a vehicle or sub-system level.

8.3. Communication Standards and Protocols

In the automotive industry bus communication systems are now standard in most types of vehicles. The following list provides some background on recent work in this area:

- CAN (Controller Area Network) (ISO 11898) `http://www.can.bosch.com` is found in many vehicles today. It is a family of protocols and it is not unusual to see vehicles with up to five different CAN buses for different purposes.

- LIN (Local Interconnect Network) `http://www.lin-subbus.org` is a cost efficient bus for low requirement applications.

- TTP (Time Triggered Protocol) `http://www.ttagroup.org` is designed to be used in demanding, safety-critical applications such as brake-by-wire and steer-by-wire.

- FlexRay `http://www.flexray-group.com` is a competitor to TTP. Leading actors as BMW, DaimlerChrysler, Motorola, Philips, GM, and Bosch promote FlexRay for its high bandwidth, availability, flexibility, deterministic behaviour, and fault tolerance.

- MOST (Media Oriented Systems Transport) `http://www.mostcooperation.com` is an optical bus for high bandwidth applications, primarily aimed for infotainment.

9. CONCLUSIONS

Automotive safety systems rely on accurate estimation of external and internal state variables as well as unobserved environmental parameters as friction and tire pressure. We have in this contribution surveyed the main needs for signal processing development and argued for a sensor fusion approach where all tasks are considered jointly. First, Section 2 summarized a number of safety systems, and it was pointed out that a limited number of sensors can be sufficient to implement a variety of safety systems. Second, the active development of improved communication networks enables new sensor fusion strategies.

Figure 16 extends Figure 9 and summarizes our view on sensor fusion for future automotive safety systems. All available sensor information is communicated to the centralized or distributed sensor fusion algorithm. This includes vision sensors (camera, radar, lidar, IR), an inertial measurement unit (IMU) with up to three accelerometers and three gyroscopes, satellite navigation, and, most importantly wheel speeds. The curved coordinate system aligned to the road and the state space model (19) is the sensor fusion glue between the different kind of sensors and applications. The output from the sensor fusion include virtual sensor signals, navigation information, tracking information and road ge-

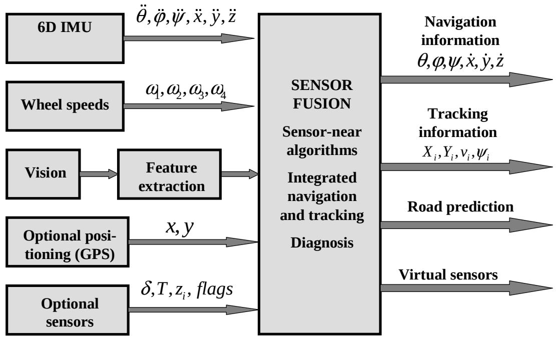


Fig. 16. Sensor fusion in future vehicles?

We have pointed out signal processing challengs ranging from low level sensor-near pre-processing to the high-level algorithms for situational awareness. These are needed in advanced driver assistance systems for decision support, feedback control and driver alerts. Model-based control systems is one particular example, where signal processing design becomes particularly integrated with control system design.

10. ACKNOWLEDGEMENT

My work in automotive signal processing started with tire-road friction estimation in the European union project *Prometheus*, 1992-1994, with Volvo Car Corp. Five years later, I co-founded the company NIRA Dynamics for commercializing the results of this project, and quite soon general projects on automotive sensor fusion functions started. I have also had a long-term collaboration Volvo Car Corp. regarding collision avoidance systems. These two companies must first of all be acknowledged, and, in particular, the CEO of NIRA Dynamics, Dr. Urban Forssell, has contributed with background facts on several issues. These two collaborations have been supported by grants from Vinnova's competence center ISIS and the IVSS (Intelligent Vehicle Safety Systems) program, which are also acknowledged. This paper also contains partial results from projects with grants from the Swedish Research Council (Sensor Fusion and Sensor Informatics) and the European Union (FP5-IST-002013) project MATRIS.

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