A View of Automotive Control Systems

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ABSTRACT: Control of automotive vehicles and engines is a relatively new field in automatic control. Some current applications for engine control are described. Future nonlinear and time-varying automotive systems will require the development of more advanced control schemes. Representative examples for plant modeling, parameter and state estimation, and adaptive control are presented.

Introduction

Today's advanced automotive systems, such as engines, transmissions, active suspension systems, and brakes, are controlled by microcomputers. Introducing automatic control into these systems, one has to cope with nonlinear plant characteristics, time-varying parameters, and fast dynamics. Some variables essential for the control scheme cannot be measured at all. Thus, automotive systems are a major new challenge for control engineers.

At present, automatic control is used to enhance performance of cars currently in production. Precise control of the air-to-fuel (A/F) ratio is required to efficiently utilize catalytic converters to minimize exhaust emissions. Knock control is carried out mainly by using heuristic procedures, taking partial advantage of self-adaptive schemes. Idle speed control has been implemented with conventional proportional-integral-derivative or with more advanced state-space control, additionally relying on real-time models of the intake manifold.

Further gains in performance require introduction of modern control theory into these applications. However, estimation procedures for state variables as well as for model parameters must be advanced to encourage their usage in real systems. Limited performance, even of future microcontrollers, restricts computational complexity. Rapid plant changes to different operating points lessen the prospects for finding an acceptable compromise between closed-loop stability and tracking performance. Increasingly integrated automotive systems will be handled by multivariable or hierarchical multilevel control approaches.

Present Control

The application of electronic control of engines has allowed a substantial reduction in emissions of toxic exhaust gases and improved drivability and specific fuel consumption. This section discusses control of fuel ratio, knock control, and optimal fuel consumption.

Lambda Control

Gasoline engines must get a proper mixture of air and vaporized fuel to burn efficiently. The A/F ratio is called lambda (λ) and is calculated as follows, where \( m_a \) is the mass airflow into the engine, \( m_f \) the metered fuel mass, and \( L_\text{ST} \) the A/F mass ratio of stoichiometric mixture.

\[
\lambda = \frac{m_a}{m_f} \frac{1}{L_\text{ST}} \tag{1}
\]

Lambda is normalized to be 1 at stoichiometric operation. While the driver regulates the amount of air, \( m_a \), going into the cylinders, the correct quantity of fuel, \( m_f \), must be added by the electronic control unit. Due to incomplete fuel evaporation, gas turbulence in the combustion chamber, and the limited time available, the burning process is nonideal, even at stoichiometric mixtures. Poisonous carbon monoxide, hydrocarbons, and, simultaneously, nitrogen oxide are generated in addition to nontoxic carbon dioxide and water vapor. The dangerous components may be oxidized and reduced by means of a catalytic converter, which is built into the exhaust pipe system. The converter operates, however, only if the A/F ratio lambda is controlled precisely to stoichiometry. The average lambda offset must be kept below 0.1 percent. In the case of engine transients, short excursions may be tolerated up to 3 percent.

With the help of a so-called lambda sensor, the A/F ratio in the exhaust pipe can be measured. The sensor generates a voltage showing a steep gradient in the area of lambda equal to 1. Hamburg and Shulman [1] have shown that, in this application, the engine may be described by a simplified model, consisting of a delay time \( T_D \) and a lag time \( T_L \). These times vary with the engine's operating condition in the range of delay time \( T_D \) approximately equal to from 100 msec to 1 sec and lag time \( T_L \) approximately equal to from 50 msec to 0.5 sec. The variation is considered in the controller by respectively adapting its parameters. The block diagram of the entire control loop is shown in Fig. 1.

Due to nonlinearities and delays, a limit cycle of lambda near the nominal value appears. If the size of control parameter \( T_D \) is approximately matched to lag time \( T_L \), then the frequency of the limit cycle \( \omega_L \) is determined exclusively by the delay time \( T_D \).

\[
\omega_L = \frac{\pi}{(2T_D)} \tag{2}
\]

The integration time \( T_I \) depends on the still tolerable amplitude \( A_L \) of the limit cycle

\[
T_I = \frac{(8\pi^2)}{(K_M K_I A_L T_D)} \tag{3}
\]

The control results of the A/F ratio lambda

![Fig. 1. Block diagram of lambda control][1]

[1] Presented at the 1987 IFAC World Congress, Munich, Federal Republic of Germany, July 26-31, 1987, and published in the Congress Proceedings. This work was done while the author was with Robert Bosch Corporation, Stuttgart, Federal Republic of Germany. Uwe Kiencke now works at Siemens Corporation, Siemensstr. 10, D-8400 Regensburg 1, Federal Republic of Germany.
lambda controller. The lambda signal before the catalytic converter oscillates within the desired range. The lambda controller is kept very precisely to stoichiometric 1 in stable operating points of the engine. The performance of this control scheme has been enhanced further by the introduction of an adaptive open-loop control map [2]. If, over the vehicle’s lifetime, open-loop control electronics drift away in different operating points, closed-loop control has to compensate. The integration time $T_R$ of the controller must not be reduced below the limit given by Eq. (3), resulting in a temporary mismatch of A/F ratio during engine transients [Fig. 3(a)]. An adaptation of the open-loop control, derived from the closed-loop controller output signal, reduces the duration of these transient phases [Fig. 3(b)].

The correction values for every operating point of the engine are “learned” into a control map that is stored in a nonvolatile memory. Figure 3 shows the benefits of this approach for a vehicle during part of the Federal Test Procedure emission test cycle. The closed-loop controller no longer has to compensate for the mismatches if the learning map already takes care of them.

**Knock Control**

In gasoline engines, an unburned part of the A/F mixture within the combustion chamber may autoinflame prematurely. This phenomenon is called knocking, because it generates resonating gas oscillations that can be heard as knocking and threaten to destroy the engine [3]. The flammability of gasoline depends on:

- temperature
- pressure
- compression ratio
- time duration under stress
- fuel quality

A forward-loop control cannot consider all these influences. Closed-loop knock control provides a more accurate compensation by regulating the ignition angle or the boost pressure in turbo engines [4]. Alternatively, knocking can be measured by:

- cylinder pressure,
- engine block vibrations,
- ion current through gas mixture,
- light emission within the combustion chamber.

Regardless of the adopted measurement technique, knock-induced modulations of the signal are band-pass filtered. In case of knock detection, the ignition angle is retarded by $\Delta \alpha_k$ (Fig. 4), postponing the thermodynamic process and thereby reducing maximum cylinder pressure and temperature. Without the occurrence of knocking, the ignition angle is again gradually advanced along a slope $\frac{d\alpha}{dt}$.

By heuristically adjusting $\Delta \alpha_k$ and $\frac{d\alpha}{dt}$, the average knocking frequency and transient behavior of the control are determined. The ignition angle oscillates around an average retardation value, always approaching the knock limits under different operating conditions of the engine.

The efficiency of knock control also can be improved by adaptation. However, unlike lambda control, procedures globally effective in all the engine’s operating points have not been found as yet. In [5], Kiencke and Cao have derived an adaptation scheme that
takes into account a statistical analysis of the individual driver’s habits in different operating points.

**Self-Optimizing Control of Fuel Consumption**

If a gasoline engine is operated with constant output torque and speed, fuel consumption may be minimized by increasing the amount of intake air up to an optimum value. The stationary behavior of the engine thus may be characterized by a quadratic function of specific fuel consumption over air. The aim is to operate the engine on the lean side at minimum fuel consumption.

The optimum operating condition of the engine may be found by superimposing an orthogonal test function \( \Delta m_L \) (air modulation) to the intake air \( m_L \) and cross-correlating it with an output signal \( \frac{d\theta}{dt} \) proportional to engine torque (Fig. 5). The result of the correlation contains the gradient of the quadratic function as part of the engine model.

\[
U(t) = \frac{1}{T_1} \int_{t-T_0}^{t} \Delta m_L [t - (\omega t)] \cdot \left( \frac{d\theta}{dt} \right) dt
\]

The gradient is regulated to zero by integral control. A problem in applying this self-optimizing control has turned out to be the slow response time of engines. The intake air may be modulated no faster than about 2 Hz. If a sufficiently large correlation time constant \( T_m \) is provided, the controller time constant goes up to \( T_c = 30 \) sec. Therefore, applications are limited to learning control of open-loop engine maps.

**Advanced Control**

Advanced modern control can improve performance and provide more systematic approaches, such as:

- Plant modeling
- Parameter and state estimation
- Adaptive and robust control
- Hierarchical, decentralized control
- Intelligent control

**Plant Modeling**

It is well known that, prior to controller design, the dynamic behavior of the respective process must be analyzed. This requires derivation of a model that describes process properties to sufficient accuracy. In automotive systems, the modeling job turns out to be far more difficult and time-consuming than the design of the controller itself. Some models currently in use only address static plant behavior; for example, so-called engine maps have been introduced to optimize A/F ratio and ignition angle in each operating point of the engine (Fig. 6). The ignition angle is stored for all combinations of engine speed and basic fuel-injection timing. After having determined its present operating point, the ignition controller reads out the optimum ignition angle from the map.

Böising and coworkers [7] and Tennant and coworkers [8], [9] developed a computerized procedure to get the optimum values, which is based on the method of Lagrangian multipliers. By this, the engine’s fuel consumption is minimized while regarding given constraints for pollutants.

Unfortunately, such static models only partially describe transient behavior of the engine. Currently, only a few useful dynamic models exist [10]–[15]. This is due to the problem that models tend to become very complex to match well the physical behavior of the plant; for example, an engine process is comprised of the following disciplines:

- Aerodynamics
- Thermodynamics
• flame propagation
• chemical reaction
• mechanics

Automotive engineers have the unpleasant decision of either simplifying models for easy handling, at the risk of unduly reducing their validity, or else leaving models rather complex, being unable to parameterize them for the real world. Plants are usually extremely nonlinear, time variant, and coupled. Since control synthesis is based primarily on linear, time-invariant theory, models have to be linearized around operating points. By doing this, an additional dependence on operating-point characteristics is introduced.

One way to overcome these problems may be to combine partially dynamic models with static control maps. Kiencke and Schulz [16] have derived a model, describing the airflow intake manifold of a gasoline engine (Fig. 7). For simplification, the intake manifold will be regarded as a concentrated element, where local pressure distribution and pulsations are not considered. Fuel is injected on top of the intake valves of the engine, assuming the gas in the intake manifold to be ideal. The quantity of heat necessary to evaporate fuel will be provided completely by heat conduction from the engine. State transitions of the gas inside the intake manifold are then considered as adiabatic. The energy balance describes the alteration of the specific inner energy \( u \), inherent to the air mass \( m \), within the intake manifold volume \( V \), due to the specific enthalpies \( h_a \) and \( h_o \) of in- and outflowing air \( m_i \) and \( m_o \) as

\[
\frac{d(m \cdot u)}{dt} = m_i h_i - m_o h_o \quad (5)
\]

Execution of differentiation and introduction of air density \( \rho \), ambient and manifold temperatures \( T_a \) and \( T_m \), and specific heats \( c_p \) and \( c_v \) results in

\[
\rho \cdot \dot{T}_m + \dot{T}_m \cdot \rho = (c_v/c_p) \left( \frac{1}{V} \right) \cdot (m_i T_a - m_o T_m) \quad (6)
\]

The ideal gas law is applied to this expression, yielding

\[
\rho_i = (\alpha R T_i/V) \left( m_i - m_o T_m/T_i \right) \quad (7)
\]

The inflow \( m_i \) shall be measured, e.g., by an airflow meter. Taylor [17] has approximated outflow \( m_o \) from the manifold into the engine employing two constants \( K_2 \) and \( K_3 \), which depend on the engine’s operating points and the exhaust gas pressure, respectively.

However, this frequently employed formulation is not accurate enough for use over the engine’s entire operating range. A reason may be the variable backflow of burned gases into the manifold through the open intake valve, which has not been considered in the preceding approach. Improved model validity can be obtained if the outflow is given by a static control map

\[
m_o = f(a, p) \quad (8)
\]

which is determined by engine test-bed measurements at stationary airflow. The dynamic behavior of the resulting model

\[
\dot{n} = \frac{1}{V} \left( m_i - m_o \right) T_m/T_a \quad (9)
\]

is dominated by the time constant

\[
T_m = V/(\alpha R T_i) \quad (10)
\]

A mechanical model, not detailed in this paper, completes the description of engine performance. The comparison of manifold pressure and engine speed shows excellent tracking between estimated and measured values (Fig. 8). The preceding model has been introduced successfully into state-space control of engine idle speed, enabling removal of an additional manifold pressure sensor [16].

R. I. Morris and coworkers [18] and T. Takahashi and coworkers [32] have taken an alternating approach by employing a black-box model. Such models may be used for control synthesis in some areas. However, they never reproduce physical relationships within the process, which are essential for model validation and diagnostics. Therefore, it is recommended that black-box models be applied only if a physical model cannot be obtained.

Parameter and State Estimation

Assuming the availability of a suitable model, it has to be parameterized. If processes are linear and time invariant, an obvious approach would be to determine parameters in an off-line configuration [19]; for example, an engine might be excited on the test bed with input test functions while monitoring output values. Well-known methods, such as correlation techniques, Fourier analysis, and pulse or step response, apply here. Unfortunately, off-line techniques poorly cover most nonlinear, time-variant automotive applications. Even in cases where fixed parameters might be a good start, an automated offset for manufacturing tolerances and aging is required. Therefore, recursive on-line estimation procedures are favored in conjunction with adaptive control.

Out of a large variety of recursive on-line estimation methods [20], only a few are suitable for automotive applications. Contrary to chemical processes, time constants within the engine, transmission, and antiskid brake systems are orders of magnitude smaller, starting in the range of only milliseconds. Therefore, algorithms for parameter estimation must converge very rapidly. At the same time, closed-loop stability must be maintained. Further complicating the situation, limited performance even of future microcontrollers constrains computational complexity of estimation algorithms.

Cao et al. have given an overview of identification methods for automotive applications [21]. A recursive least-squares (RLS) algorithm has been extended to identify
The gain be formulated as

\[ \hat{\beta}(k + 1) = \hat{\beta}(k) + r(k + 1) e(k + 1) \]  

(11)

The gain \( r(k + 1) \) may be calculated as shown, where \( \beta(k) \) is the vector of actual input and output values.

\[ r(k + 1) = \lambda(k) \beta(k)/[1 + \beta^T(k) \lambda(k) \beta(k)] \]  

(12)
The error of real versus estimated output is

\[ e(k + 1) = y(k + 1) - \hat{y}(k + 1) \]  

(13)
The covariance matrix is updated according to

\[ \lambda(k + 1) = \lambda(k) - r(k + 1) \beta^T(k) \lambda(k) \]  

(14)

For clarity, \( \lambda(k + 1) \) will be alternatively expressed as

\[ \lambda(k + 1) = \lambda(k)/[1 + \beta^T(k) \lambda(k) \beta(k)] \]  

(15)

which allows conversion of Eq. (11) to

\[ \hat{\beta}(k + 1) = \hat{\beta}(k) + \lambda(k + 1) \beta(k) e(k + 1) \]  

(16)

The elements of the covariance matrix \( \lambda(k + 1) \) may be interpreted as weighting factors, determining the impact of measured values \( \beta(k) \) and error \( e(k + 1) \) on the convergence rate of estimation vector \( \hat{\beta}(k) \). Equation (15) shows that the elements of \( \lambda(k + 1) \) decrease continuously during the estimation procedure. Finally, convergence rates become very low, which can be tolerated only in the case of fixed parameters.

However, the requirement was to identify time-variant parameters. Therefore, the preceding scheme must be modified—e.g., into

- RLS with forgetting factor [22], [23],
- RLS with moving window [24],
- RLS with resetting [25].

Returning for a moment to nonrecursive least squares, the covariance matrix may be formulated as

\[ \lambda(k) = [M(k) M^T(k)]^{-1} \]  

(17)

with \( M(k) \) being the concatenation

\[ M(k) = [\beta(0), \beta(1), \cdots, \beta(k - 1)] \]  

(18)
of vector \( \beta \) for measurement values.

Advancing from \( k \) to \( k + 1 \), the latest vector \( \beta(k) \) is added to \( M(k) \), leading to

\[ M(k + 1) M^T(k + 1) \]

\[ = M(k) M^T(k) + \beta(k) \beta^T(k) \]  

(19)

Running through the recursion steps, \( M(k) \) is continuously enlarged, resulting in decreasing elements of \( \lambda(k) \) [Fig. 9(a)]. RLS with forgetting factor introduces a factor \( \lambda_F \) into Eq. (19). Vector \( \beta \) within matrix \( M(k) \) is thus exponentially decreased versus time, emphasizing recent measurements [Fig. 9(b)].

\[ \lambda(k + 1) = (1/\lambda_F) [\lambda(k) - r(k + 1) \beta^T(k) \lambda(k)] \]  

(21)

Increasing the elements of the covariance matrix \( \lambda(k + 1) \) over those in RLS. Usually the forgetting factor \( \lambda_F \) between 0.95 and 1.0 is chosen. However, it may be preferable to have \( \lambda_F \) depending on error \( e(k) \) to avoid a blow-up effect [26], [27]. Fortescue et al. [22] have proposed that

\[ \lambda_F = 1 - (\varepsilon^2(k) \Sigma_n)^{1/2} \]  

(22)

with constant \( \Sigma_n \) being determined by application events. Thus, \( \lambda_F \) is decreased below one, when parameter transients are indicated by a large error \( e(k) \), and is almost equal to one in steady situations with small errors.

RLS with “moving window” deletes the measurement vector \( \beta(k - m) \) from matrix \( M(k) \) while introducing a new vector \( \beta(k) \). Thus, a moving observation window on the latest \( m \) vectors \( \beta(k) \) to \( \beta(k - m + 1) \) is formed [Fig. 9(c)]. In some cases, a combination of RLS with both forgetting factor and moving window has been considered [Fig. 9(d)].

In some automotive applications, RLS with resetting has delivered promising results. After a given number of recursion steps, the time scale is reset to its initial value. The last estimated parameter vector \( \hat{\beta}(k) \) is taken over as the initial value \( \hat{\beta}(0) \) into the next calculation interval, while the covariance matrix \( \lambda(0) \) is reset to an initial diagonal matrix. The original RLS algorithm as stated earlier is restarted repeatedly, using Eqs. (11)–(15). A “fall-asleep effect” of plain RLS thus can be overcome efficiently without endangering stability.

Comparative results of the different approaches are shown in Fig. 10. The friction coefficient between the tire and the road surface at one of a car’s wheels is recursively

\[ \hat{\beta}(k + 1) = \hat{\beta}(k) + \lambda(k + 1) \beta(k) e(k + 1) \]  

(16)

\[ \lambda(k) = [M(k) M^T(k)]^{-1} \]  

(17)

\[ M(k) = [\beta(0), \beta(1), \cdots, \beta(k - 1)] \]  

(18)

\[ \lambda_F = 1 - (\varepsilon^2(k) \Sigma_n)^{1/2} \]  

(22)
estimated during an antiskid braking procedure. After about half a second, the condition of the road surface changes almost stepwise. RLS with resetting is tracking this with a lag time of under 100 msec.

State-variable estimation also is required frequently in automotive control systems. In an example presented earlier [16], manifold pressure was obtained from a model rather than an additional sensor. In state-space control, only part of the state variables may be accessible. State-variable estimation allows for substantial cost savings by replacing measurement devices. The usual way to handle this task is to apply a Kalman filter [28]-[30] or Luenberger observer [31]. Takahashi and coworkers [32] have employed an observer for idle speed control. There are a number of problems to overcome in real application:

- In order to estimate state variables, the structure and parameters of the process model have to be accurately known. Obviously, this precondition is not always met.
- In Kalman filtering, statistical characteristics of input and measurement noise must be known. However, in some applications, statistical data are assumed arbitrarily, without any reference to the real situation.

As a consequence, state-variable estimates differ from real values, making such approaches less attractive. Proposals to overcome these problems are adaptive Kalman filtering [33], [34] or heuristic handling of statistical data [35], [36]. However, results are not always satisfactory. Further progress is still necessary in this area.

Another application of estimation procedures in automobiles is early diagnosis of emerging faults [37], [38]. Based on a validated model, system parameters and/or state variables are estimated continuously. An emerging fault can be detected by checking whether estimated values are within their tolerate reference range. The difficulty is to find a trade-off between high sensitivity—eventually triggering false alarms—and low sensitivity—risking not detecting faults at all. As many more sophisticated electronic systems will be installed into automobiles, proper design of early fault-diagnosis systems will be a major challenge for control engineers in the future.

**Adaptive and Robust Control**

Assuming the existence of a model with sufficiently accurate parameters, adaptive control schemes can be applied. Robust control is another way to regulate plants with only slight parameter variations, if a controller with constant parameters is acceptable [39].

Cao et al. [21] have investigated an adaptive cruise control for vehicles, which relieves the driver from regulation at a given speed. For different engine types, transmission gears, and loading conditions, plant parameters vary significantly. Characteristics of engine output torque and air drag are nonlinear. Conventional proportional-integral control performs rather poorly in this situation.

A model for cruise control is shown in Fig. 11. Here, \( K_F \) is the amplification factor of the engine torque map determined by testbed measurements, \( i_g \) and \( i_r \), the transmission ratios of the gearbox and the drivetrain, \( \tau_E \), the transmission efficiency, and \( r \), the wheel radius. The subtraction of different load forces from the driving force \( F_d \) yields the accelerating force \( F_a \), which is integrated into vehicle speed \( v \). The time constant \( T_v \) is proportional to the effective mass of the vehicle, which also covers rotational movements of the drivetrain. The air drag force is calculated from the vehicle speed \( v \), the wind velocity \( v_w \), the air density \( \rho_a \), the drag coefficient \( c_w \), and the sectional area \( A \).

The linearization of the model in operating points \( U_0 \) and \( V_0 \) leads to a first-order system with variable parameters, with output signal (speed), \( y(t) \) the state variable, and control signal (throttle angle) \( u(t) \), proportional factor \( K \), time constant \( T \), and \( \epsilon \) summarizing all disturbances.

\[
Ty'(t) + y(t) = Ku(t) + \epsilon \\
y(t) = V(t) - V_0 \tag{23}
\]

\[
u(t) = U(t) - U_0 \tag{24}
\]

\[
K = K_F i_g i_r / \left( \rho_a c_w A v_w \right) \tag{25}
\]

\[
T = T_v / \left( \rho_a c_w A v_w \right) \tag{26}
\]

After introduction of variables \( a_1 \) and \( b_1 \), this can be transferred into a time-discrete description.

\[
y(k + 1) = a_1 y(k) + b_1 u(k) \tag{28}
\]

\[
a_1 = \exp (-T_{\text{sample}}/T) \tag{29}
\]

\[
b_1 = V(1 - a_1) \tag{30}
\]

The disturbances are contained in parameter \( b_1 \). For control, a one-step-ahead controller that minimizes the cost function \( J \) is adopted because of its extraordinary simplicity.

\[
J = p[w(k + 1) - y(k + 1)]^2 + qv^2(k) \tag{31}
\]

The control law can be stated as shown, where \( w(k + 1) \) is the reference vehicle speed.

\[
u(k) = \left[ \rho_a c_w A v_w / (p + q \rho_a c_w A v_w) \right] \left[ w(k + 1) - a_1 y(k) \right] \tag{32}
\]

Model parameters \( a_1 \) and \( b_1 \) are estimated.
Fig. 12. Adaptation of controller amplification to different loading situations in cruise control [21].
continuously, e.g., by RLS, and then entered into Eq. (32).
Figure 12 shows a representative result from field experiments in the car. The controller’s amplification factor
\[ p b_i(q + p b^2) \] (33)
readily adapts to transients between loading and unloading, simulated by pulling manual brakes. Vehicle speed deviates only slightly in these situations, proving good practical performance of adaptive control. Other advantages are as follows:
- covering a broad range of vehicle types with only one basic controller,
- significant reduction of application work, and
- self-tuning against aging during the car’s lifetime.

Hierarchical, Decentralized Control

In advanced cars, a number of electronic control subsystems are implemented, such as engine control, transmission control, performance control, antiskid braking control, suspension control, etc. Until recently, these systems operated mostly on a stand-alone basis. Since all subsystems are coupled via the car itself, the control activities in one individual subsystem can generate undesired cross influences within the others. To overcome such effects, an additional optimization control layer must be introduced, operating in addition to already existing subsystems. This leads to a distributed multimicrocomputer system in the car.

For implementation, Robert Bosch GmbH has announced a new automotive communication link called “controller area network” (CAN), which provides not only communication between subsystems but also supports parallel processing in distributed controllers [40], [41]. CAN provides basic mechanisms for process synchronization and consistent data handling. User programs in the individual controllers are efficiently unloaded from the communication job itself. For each message, a communication object is created, which consists of the following:
- Identifier, naming and routing the message;
- Control segment, containing all transfer control information; and
- Data segment, ranging from 0 to 8 bytes.
User programs may access communication objects in the communication buffer as in any ordinary random access memory at predefined locations. Thus, a virtual communication channel is provided for each individual message on the application layer, whereas network control is hidden from the user. Built-in CAN features include:
- error detection,
- error correction,
- failure localization, and
- automatic truncation of faulty nodes.

Time for recovery from error is very short, with 25 bit times only.
The following example for an integrating control system makes use of the preceding communication type (Fig. 13). There are two separate electronic subsystems for engine and transmission control. Under certain driving conditions, the entire drivetrain might jerk. For relief, an additional control hierarchy is introduced, which employs engine load and engine, drivetrain, and vehicle speeds as inputs, and superimposes a correction on engine performance. Control programs are localized both in the engine and transmission subsystems. Measurement values and control signals are transmitted via the serial communication link.

The advantage of decentralized control is an improved availability of the overall system in case of failures; for example, in case of a failure in the transmission control computer, the transmission shifts into the highest gear. The car is still operational although with degraded functionality. Contrary to a centralized arrangement, engine control is not affected at all.

Intelligent Control

Controller synthesis as discussed thus far in this paper has been based on analytical models. Design methods have been aimed at
- optimization of a cost function,
- guarantee of stability,
- preassignment of dynamic behavior, etc.

Fig. 13. Distributed vehicle control with parallel controllers [40], [41].
As mentioned earlier, models of automotive systems sometimes may be difficult to derive or complicated to handle. In such cases, intelligent control might be an alternate method of increasing control efficiency. Learning A/F ratio control, discussed earlier, is considered to be a first pragmatic step in this direction.

In the future, such approaches must be developed more systematically, making use of pattern recognition [42], [43], expert systems [44], and fuzzy control [45], [46]. It is hoped that these methods will bridge the gap between traditional control and data-base orientation in the field of artificial intelligence.

Conclusion
In order to improve performance of automatic control in automotive systems, more advanced control schemes involving modeling, parameter and state estimation, and adaptation will be applied. An overall optimization layer combining all electronic systems will further improve driving safety and economy. To handle nonlinear and time-varying automotive systems, additional progress in control engineering is needed, especially in the areas of state-variable estimation and intelligent control.

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References

**1988 CDC**

Arrangements are proceeding for the 1988 IEEE Conference on Decision and Control (CDC) to be held Wednesday through Friday, December 7-9, 1988, at the Hyatt Regency Austin on Town Lake, Austin, Texas. As usual, the conference will be conducted in cooperation with the Society for Industrial and Applied Mathematics and the Operations Research Society of America.

In the accompanying photograph, General Chairman Mike Polis proposes a toast to the success of the CDC, which will feature interesting technical presentations in an interesting setting. For those who appreciate elaborate architecture, also pictured is a historic home in the Bremond block of downtown Austin.

The conference emphasizes all aspects of the theory and applications of systems involving decision, control, optimization, and adaptation. For further information, contact the General Chairman:

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Uwe Kiencke was born in 1943 in Oldenburg, Federal Republic of Germany. He received a degree in communications engineering from Karlsruhe University in 1967 and a doctoral degree in control engineering from Braunschweig University in 1972. From 1972 to 1987, he was employed at Robert Bosch Corporation in Stuttgart, where he was involved in the advanced development of automotive control systems and digital LSI circuits such as an automotive real-time microcontroller. He headed the team that developed the serial automotive communication network “controller area network.” In 1988, he joined Siemens Corporation in Regensburg and is currently Department Manager for design of the electronic engine control unit. He lectures at Kaiserslautern University on “Control and Signal Processing in Automotive Systems.”