Dynamic Monocular Machine Vision

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Abstract: A new approach to real-time machine vision in dynamic scenes is presented based on special hardware and methods for feature extraction and information processing. Using integral spatio-temporal models, it bypasses the nonunique inversion of the perspective projection by applying recursive least squares filtering. By prediction error feedback methods similar to those used in modern control theory, all spatial state variables including the velocity components are estimated. Only the last image of the sequence needs to be evaluated, thereby alleviating the real-time image sequence processing task.

Keywords: 4-D machine vision, real-time image sequence processing, automatic visual motion control, vehicle guidance

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1. Introduction

Dynamic vision is more than fast processing of static image sequences. The dynamics aspect rests primarily in the scene observed or in the motion of the sensor and is independent of the image frequency; as in any sampled measurement process, high sampling rates are necessary for recovering highly dynamical changes. In vision, however, in addition to this, high sampling rates reduce the so-called correspondence problem, that is, keeping track of special image features or objects in space from one frame to the next.

Note that humans, when talking about dynamic scenes, do not converse in image terms but do prefer spatial interpretations, both in position and velocity, whenever possible. They try to see motion of objects in space. Motion properties of objects are an integral part of a person's knowledge base like possible shapes and colors. Similarly in the approach described below, a direct spatial interpretation of image sequences is achieved by using spatial and temporal models in conjunction. This unified approach in space and time is the core of the 4-D method developed and tested for machine vision. Applications are discussed in a companion paper (Dickmanns and Graefe 1988, this issue; p. 241).

The immediate inclusion of temporal aspects is very essential since it allows a proper definition of state variables and the introduction of temporal continuity conditions for image sequence interpretation by exploiting differential equations. Geometric shape descriptions and generic models for motion *together* constitute the basis for an integrated spatio-temporal approach, which may be termed "4-D vision" or "dynamic vision."

This means that not just objects are being seen but motion processes of objects in space and time. Note that unlike "static" image sequence processing, dynamic vision has no separation between spatial object recognition from one frame to the next as a first step and motion reconstruction afterwards as a second one. Instead, object and motion are treated as a unit and the least squares fit for determining the best estimate for the object motion state, based on noise corrupted image sequences, is done in space and time simultaneously.

As a very beneficial side effect, the need for storing past images (e.g., for computation of displacement vector fields or optical flow) is reduced. The state of the scene observed is represented on a very high symbolic level by the shape descriptors and the spatio-temporal state variables including spatial ve-

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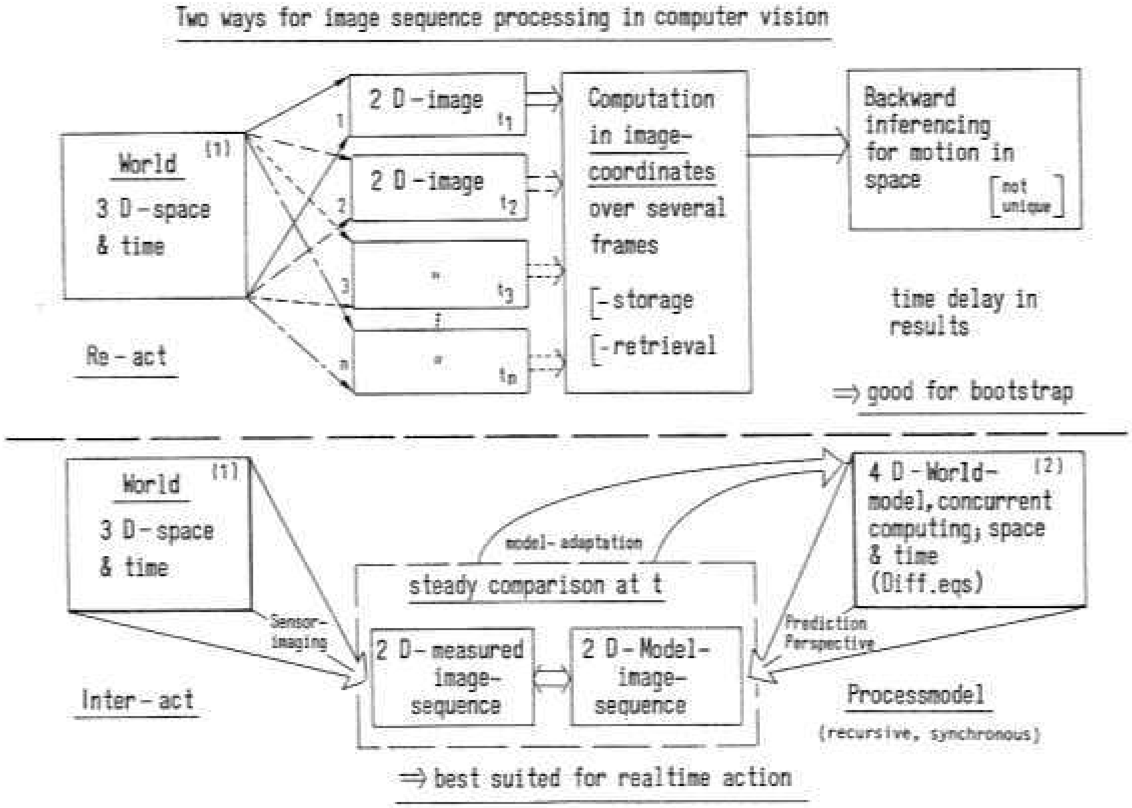

Figure 4. Two basically different methods of image sequence processing.

terwards; instead, all interpretation is immediately performed in the 4-D space–time continuum.

Similar to using shape models for object recognition, temporal models appear to be of great advantage for motion parameter recognition: As the term *re*cognition tells, the interpretation process does have background knowledge of what it is going to "see," at least as a generic class from which special objects are being instantiated through data based hypothesis generation. This usual approach for shape recognition has been augmented by associating the object with its environment and the viewing conditions for image sequence taking: If the object is at rest and the camera moves, a generic dynamical model with state variables x for the camera motion is introduced; if the camera is at rest and the object moves, a model for this motion is selected. In both cases physical motion constraints and optional control or disturbance inputs are included. (The case where both camera and object are moving is much more difficult and presently under investigation.)

The general standard form of a generic dynamical model is a set of n differential equations for n state variables, usually nonlinear, sometimes with time-varying coefficients. As in modern control theory for sampled systems, locally linearized approximations with transition matrices for the sampling period T and influence coefficients for the control are being used. All coefficients are assumed to be constant over T. This basic cycle of period T for model based measurement interpretation and control action has been selected around 0.1 s (10 Hz); the more complex situation analysis on a higher level may be slower.

The goal of basing visual process recognition on an integral spatio-temporal world model is threefold:

1. Eliminate the need to access past images
2. Determine spatial velocity components by smoothing numerical integration
3. Bypass the nonunique inversion of the perspective projection by doing recursive least squares state estimation exploiting the Jacobian matrix of the measured image features (their partial derivatives with respect to the state variables of the dynamical model).

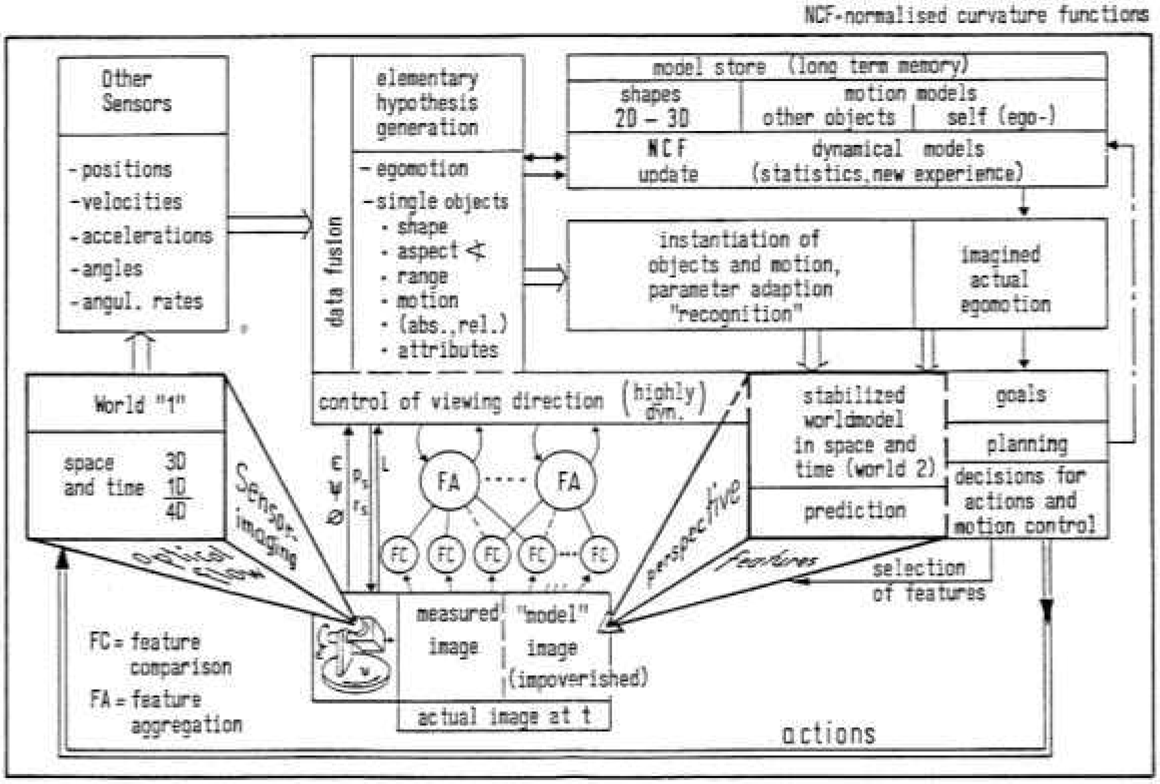

Figure 7. Block diagram of 4-D feature based vision concept including active gaze control, long term model storage, and goal driven activity planning.

(upper left), and application of motion control through effectors (bottom). Since dynamical models are available, direct state variable feedback may be used in order to achieve reflex-like behavioral competences. Thus, for example, in road vehicle guidance, lane-keeping and proper speed control may be achieved without continuously running cumbersome planning activities. Monitoring subprocesses just have to provide "road recognized" and "road free of obstacle" signals. As long as these are true and the goal is not yet achieved, the system continues in this mode. All logical variables required for mode continuation form the set of continuation control tags.

Their value, in turn, may be changed either by sensory data including situation variables derived therefrom or by decisions taken in the continuously active mission planning and monitoring subprocesses. Depending on the particular continuation control tag becoming false, specific other behavioral modes with proper sensing activities and feedback control laws, if necessary adaptable by situation dependent parameters, may be invoked, taking care of a gradual transition from the old mode to the new one.

A sufficiently rich set of behavioral modes including smooth transitions has to be developed and stored in long term memory. In addition, knowledge has to be implemented in the interpretation process as to which behavioral competences should be activated with which set of parameters, depending on the situation and the goals to be achieved.

In the long run, the system should be able to learn from statistics it accumulates during each mission. This is, however, far off in the future.

The systems we have developed up to now only have very simple reflex-like behavioral competences. Some interesting questions arise when we try to imagine what kind of behavior much more complex systems might display (in a not very near future), if they continue to be based on the general principles explained in the previous sections.

The actual world 2 instantiated in the interpretation process is forced to remain close to the real world by critical feature comparison and corresponding model adaptation based on the measured image data and the data from other real-world sensors (left column in Figure 7). What could happen if all these sensory inputs would be cut off and the central and right blocks would continue working on

Applications of Dynamic Monocular Machine Vision

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Abstract: The 4-D approach to real-time machine vision presented in the companion paper (Dickmanns and Graefe 1988, this volume) is applied here to two problem areas of widespread interest in robotics. Following a discussion of the vision hardware used, first, the precise position control for planar docking between 3-D vehicles is discussed; second, the application to high speed road vehicle guidance is demonstrated. With the 5 ton test vehicle VaMoRs, speeds up to 96 km/h (limited by the speed capability of the basic vehicle) have been reached. The test run available, of more than 20 km length, has been driven autonomously several times under various weather conditions.

Key Words: 4-D machine vision, real-time vision hardware, automatic visual motion control, vehicle docking, road vehicle guidance

1. Introduction

In the companion paper (this volume) a set of principles and methods emphasizing the dynamic aspects of machine vision have been introduced. In this paper, four applications of these concepts in the form of demonstration experiments are described, together with some technical details of the real-time vision hardware used. These experiments not only served for developing the concepts but also for convincing both ourselves and others that the concepts are indeed practical.

Simple motion control tasks in the dynamic range of a human operator, albeit confined to a visually well structured environment, were considered to be both sufficiently demanding and rewarding for the initial demonstration of practical applicability. In order to emphasize the real-time aspect, we deliberately imposed a cycle time limit of about 0.1 s (100 ms) on the interpretation and control process. This was intended to and succeeded in spurring the group to think in different terms than when time constraints do not play any role, hoping for processors to become fast enough to run any algorithm in real time. With the "real time" concept we understand two things in the context of computer vision: that the low level part of the system should sample the scene at the highest rate practical and thus process every image delivered by the TV camera, which limits the processing time for each image to 17 or 40 ms, depending on the TV standard used; and that the response time of the entire vision system (the time between some visible event in the scene and the output of a control signal which has been caused or influenced by the event) should not be much longer than for a human. Both software and hardware concepts have developed in different directions than they would have done without this side constraint; but especially the methods for information processing have shaped up differently. The real-time constraint called for recursive methods as have been developed in modern control theory. Gradually, it became clear that temporal coherence is as important as spatial coherence for visual dynamic scene analysis.

This has lead to the 4-D method presented which appears to be a natural extension of modern control engineering tools. The availability of temporally dense time histories of the spatial states including velocity components of all relevant objects in the scene provides a rich basis for inferencing and applying AI methods in the future in order to perform a more complex analysis of the situation.

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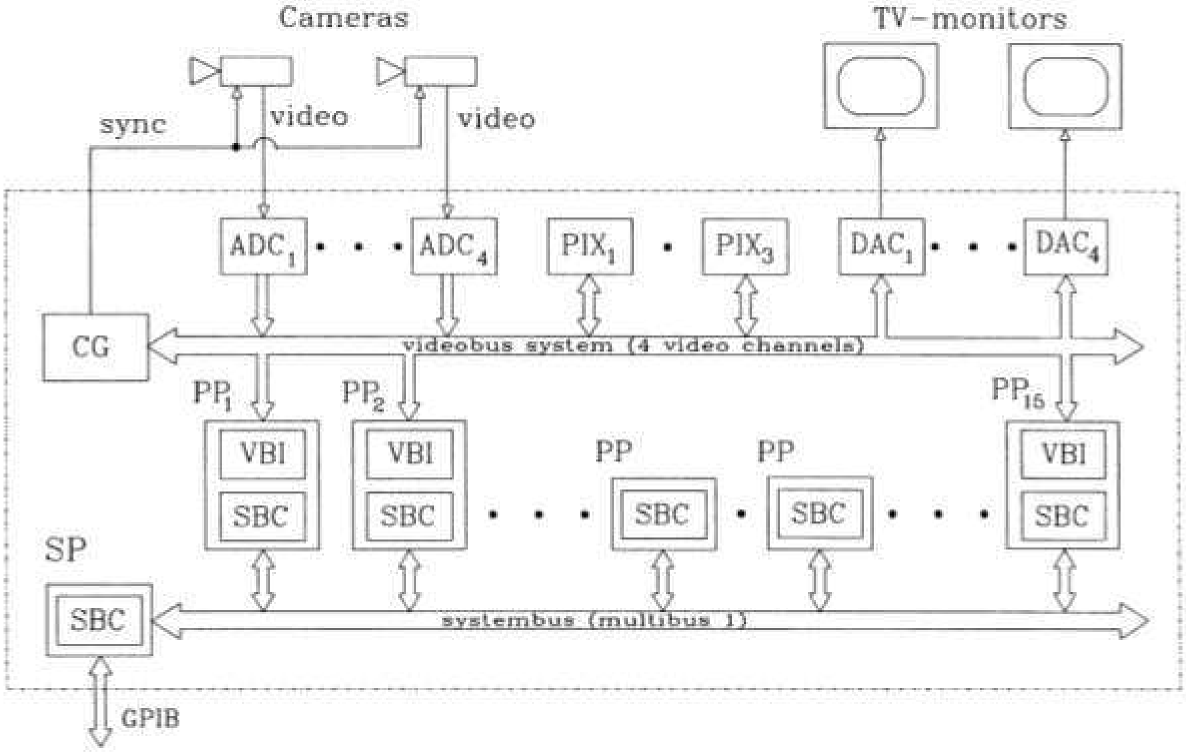

Figure 2. The second generation vision system BVV 2.

ADC:	Analog to digital converter
CG:	Central clock generator
DAC:	Digital to analog converter
GPIB:	General purpose interface bus connecting the BVV 2 to other equipment, e.g. a host computer
PIX:	Pixel processor (for preprocessing digital images on the fly)
PP:	Parallel processor
SBC:	Single board computer, based on the Intel 8086 processor
SP:	System processor (it coordinates all internal and external communication)
VBI:	Videobus interface; it reads and stores pixel data from the videobus and makes them available to the PP (not all PPs need a VBI; see text)

The total number of analog to digital converters and pixel processors is limited to 4, the number of parallel processors is limited to 15.

tions is not the sheer computing power of the processors of the BVV 2 but rather its flexibility, which allows the entire power to be concentrated on the relevant regions of the image. Optimizing the hardware by itself is, however, only part of the solution. What is really important is to optimize several things as a whole and, if possible, simultaneously: the basic methods for feature extraction, the way these methods are cast into algorithms, the hardware on which the algorithms are to be executed, and the feature based 4-D interpretation of image sequences. In reality it is difficult to optimize so many different interdependent things at the same time; a sequence of iterations is a more realistic approach.

2.3 The Future

By performing experiments in dynamic vision using the BVV 1 and BVV 2 (see chapters 3 through 5), much has been learned regarding methods and algorithms for low level vision. In 1986, as a result, a new vision system, the BVV 3, has been designed (Kuhnert 1986b; Graefe and Kuhnert 1987). The goal is to build a system which is optimized for those classes of methods and algorithms which have been found particularly useful for low level vision.

The BVV 3 will have the same structure as the BVV 2; the parallel processors will, however, be different (Figure 3). The single-board computer will now be based on the microprocessor Intel 80286; it is about two to three times more powerful and it has

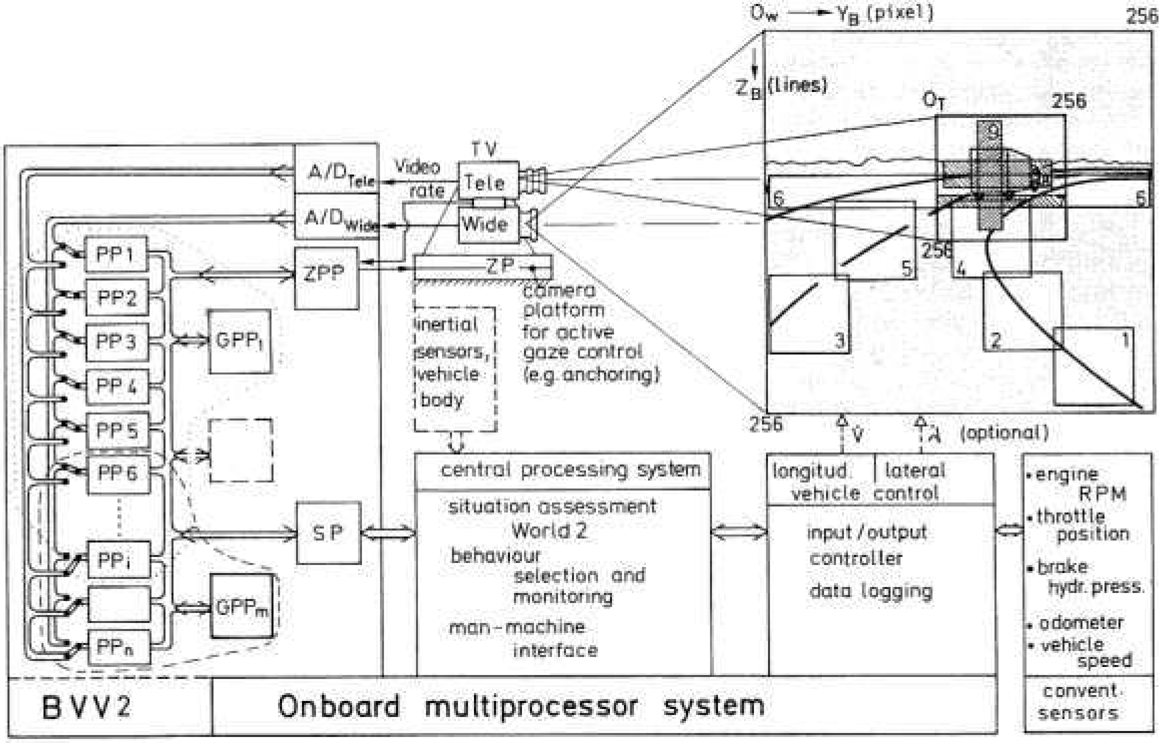

Figure 13. System architecture for a vision controlled autonomous road vehicle.

In the interpretation process, exploiting the predicted state and feature positions y^*, the incoming measurement data are screened, outliers are removed, and the image sequence analysis performed by the PPs is supervised and adjusted to the present interpretation status.

5.2 Road Model for Recursive Estimation

Here, only those parts of the visual recognition process necessary for guiding the vehicle along a free lane are given, omitting other objects and traffic information. High speed roads are modelled as a sequence of N arcs with linear curvature models defining the skeleton R of a band with constant width b. With λ as absolute and l as relative run length in each segment this may be written

$$R = \sum_{i=1}^{N} (C_{oi} + C_{li} l_i)$$
$$0 \le l_i \le \lambda_i - \lambda_{i-1} \tag{21}$$
$$C_{li} = 0 \text{ outside}$$

C_o is the constant curvature part of the model and $C_1 = dC/dl$ is the linearly varying part over arc length. The parameters of this structural model (C_{oi}, C_{li} and λ_i) have to be determined from the visual input for a certain range L in front of the vehicle.

By definition of the road model Eq. (21), using the chain rule, there follows for the curvature C_V at the location of the vehicle traveling at speed V tangentially to the road

$$\dot{C}_V = \frac{d}{dt}(C_V) = \frac{d}{dl}(C_V)\frac{dl}{dt} = C_1 V \tag{22}$$

$$\dot{C}_1 = \frac{d}{dt}(C_1) = \begin{cases} 0 \text{ on one segment} \\ V\delta(1-\lambda_i), \text{ a Dirac-impulse} \\ \text{at a transition point } \lambda_i \end{cases} \tag{23}$$

for practical purposes $\dot{C}_1$ is considered to be random noise $n_R(t)$.

These equations may be written in state space form

$$\begin{bmatrix} \dot{C}_V \\ \dot{C}_1 \end{bmatrix} = \begin{bmatrix} 0 & V \\ 0 & 0 \end{bmatrix} \begin{bmatrix} C_V \\ C_1 \end{bmatrix} + \begin{bmatrix} 0 \\ n_R(t) \end{bmatrix} = F_R x_R + v_R \tag{24}$$

Lateral dynamics. A planar "bicycle" substitution model according to Strackerjan (1975) has been applied. Two degrees of freedom are the sideslip angle β and the inertial yaw rate $\dot\psi_v$, described by the following equations of motion:

$$
\begin{aligned}
& mV\dot\beta + (U_f + U_r + \mu c_f + \mu c_r)\beta \\
& \quad - \left(mV + \mu c_f \frac{l_f}{V} - \mu c_r \frac{l_r}{V}\right)\dot\psi_v \\
& \quad = -(U_f + \mu c_f)\delta
\end{aligned}
\tag{27}
$$

$$
\begin{aligned}
& I_z\ddot\psi_v + \frac{\mu}{V}(c_f l_f^2 + c_r l_r^2)\dot\psi_v - \mu(c_f l_f - c_r l_r)\beta \\
& \quad = (U_f l_f + \mu c_f l_f)\delta
\end{aligned}
\tag{28}
$$

where I_z is the moment of inertia around a vertical axis, $c_{f,r}$ are normal side force coefficients applicable to front and rear axles. $l_{f,r}$ are the distances of the CG to the front and rear axle respectively, $U_{f,r}$ are the circumferential forces on the wheels, and μ is the friction coefficient between wheels and road. δ is the steer angle of the front wheels. In the vehicle a computer controlled stepping motor serves as actuator for steering. It has been modelled as an integrator

$$\dot\delta = k_\delta \cdot u \tag{29}$$

where $\dot\delta$ is limited to 15 deg/s.

The lateral position y_v on the road is constrained by the differential equation

$$\dot y_v = V(\Delta\chi + \delta \cdot l_r/d) = V(\psi_K - \beta + \delta \cdot l_r/d) \tag{30}$$

where $\Delta\chi$ is the path azimuth angle relative to the road, $d = l_r + l_f$ is the axle distance, and the road-oriented vehicle yaw angle ψ_K is linked to the inertial yaw angle ψ_v by

$$\dot\psi_K = \dot\psi_v - C_V V \tag{31}$$

The last term represents the temporal road heading change due to curvature C_V and vehicle speed V.

Figure 15. VaMoRs, the experimental vehicle for autonomous mobility and machine vision.

5.4 Integrated State Space Model for the 4-D Approach

The imaging Eq. (26) contains contributions both from the road (b and y_C) and from the vehicle state (y_v and ψ_K).

Combining Eqs. (26) to (31) one obtains a state space model for lateral dynamics relative to a road with visual measurements taken at the look-ahead distance L. It is of fifth order with the state variables

$$
\begin{aligned}
x^T &= (\dot\psi_v, \beta, \psi_K, y_v, \delta) \\
\dot x &= F_v x + gu + hC_V
\end{aligned}
\tag{32}
$$

where

$$
F_v = \begin{matrix} f_{11} & f_{12} & 0 & 0 & f_{15} \\ f_{21} & f_{22} & 0 & 0 & f_{25} \\ 1 & 0 & 0 & 0 & 0 \\ 0 & -V & V & 0 & f_{45} \\ 0 & 0 & 0 & 0 & 0 \end{matrix}
\qquad g = \begin{matrix} 0 \\ 0 \\ 0 \\ 0 \\ k_\delta \end{matrix}
\qquad h = \begin{matrix} 0 \\ 0 \\ -V \\ 0 \\ 0 \end{matrix}
$$

The component $\dot\psi_K$ contains a contribution due to road curvature C_V. The elements f_{ij} depend upon the parameters V, m, μ, the side force coefficients, the vehicle CG location, and the circumferential forces on the wheels.

The dominant effects caused by parameter changes are due to speed variations, which also are the most frequent ones. Adaptations to changes in mass m are—if at all—only necessary at the beginning of a mission. Changes in friction coefficient μ may be due to road surface parameters including weather conditions. Since speed is the only easily measurable variable and has the largest influence on vehicle behavior under normal conditions, its effect on the model is always taken into account, that is, the nonlinear physical model is approximated by a time-varying mathematical model with speed V governing the coefficients (Zapp 1985). In the experimental vehicle VaMoRs, speed is derived from the digital odometer system.

The two systems of Eqs. (24) and (32) may be where (several) objects of unknown shape may occur having unknown dynamical characteristics.

In order to be able to handle more complex tasks efficiently, the introduction of artificial intelligence methods on top of the 4-D state representation seems to be favorable. Note that in this approach actions are an integral part of the internal representation.

Observing and analyzing state variable time histories may provide a direct access to temporally deep reasoning including frequency domain methods.

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