Scene Recognition and Navigation Capabilities for Lane Changes and Turns in Vision-Based Vehicle Guidance.

Dickmanns E.D. and Müller N.

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Abstract: The development of autonomous visual guidance for land vehicles at UniBwM is reviewed. An initial breakthrough in performance level was achieved in 1986 by combined differential/integral representations of the road skeleton and the vehicle state in conjunction with recursive estimation techniques (4-D approach). Feedback control laws allowed easy implementation of reactive behavior; by complementing this approach with generic feedforward control-time histories for several mission elements, a capability for mission performance is introduced. Lane changes, turn-offs and handling forks in the road are the most essential such elements; in conjunction with a capability for landmark recognition and digital map reading this allows the autonomous performance of entire missions. Recently developed capabilities of the **VaMoRs** test vehicle are discussed.

Keywords:Feedforward/feedback control, navigation systems, scene analysis, symbols, visual motion

1. INTRODUCTION

The problem of road vehicle navigation by computer vision was attacked independently in the US (Klass, 1985) and in Germany (Meissner, 1982) in the early 1980s. In 1986 the first test trials with the 5-ton van **VaMoRs** were made after extensive studies in hardware-in-the-loop simulations over several years, with real-time performance as a side constraint right from the beginning. The year 1986 had brought a breakthrough in the performance level of visual road vehicle guidance, following the adoption of road skeleton representations using differential geometry, and recursive estimation techniques for road parameter and relative state estimation. This allowed short cycle times with modest requirements for computing power.

Initially, by means of direct state vector feedback to lateral and longitudinal control variables, behavioral capabilities in local environments like 'road running' (Dickmanns and Zapp, 1987) and 'obstacle avoidance' (Dickmanns and Christians, 1989) could be achieved without any planning component, merely as a reaction to the environmental situations being sensed. In this respect the system based on conventional control engineering methods behaved similarly to the subsumption architecture (Brooks, 1986). However, the 4-D approach underlying the recursive estimation techniques which were developed, with full perspective projection taken into account for mapping the spatial arrangement of objects into the 2-D image plane, allowed the motion process to be modelled along the time axis, and continuity conditions to be exploited in this very important degree of freedom. Especially, a vehicle's motion capabilities are limited and usually well known; this was exploited in order to separate systematic state changes from process and measurement noise. This approach has become standard in the meantime, though many variants can be found in the literature.

For global mission performance, it is of course not sufficient to confine scene understanding to differential aspects; integral relations over longer periods of time and many elemental maneuver sequences have to be known. In artificial intelligence, quasisteady-state representations with more theoretically defined ideal transitions have been in use in the framework of computer studies; real-world perturbation effects and measurement uncertainties were hard to deal with. Therefore, many of the abstract planning results based on ideal-world models have not been very useful in the practical situations of a dynamically changing world.

In contrast, the derivation of capabilities for the recognition of situations on the one hand, and behavioral capabilities for performing certain maneuver elements under perturbed conditions on the other (both based on spatio-temporal models of objects and typical motion processes), allows one to provide an autonomous vehicle with a practical knowledge base for flexible mission performance under real-world conditions. Only topological background knowledge, a rough plan of the sequences of subtasks, and a capability for visual landmark recognition are needed for the vehicle to reorient itself in order to achieve its desired goal.

This type of skill-based mission performance was first developed in the authors' laboratory for guiding autonomous vehicles on the factory floor (Hock, 1991); recently, it has been carried over to land vehicle mission performance on road networks (Hock, 1994). In the latter domain the Global Positioning System (GPS) is utilized in conjunction with inertial and odometric sensor data, as well as visual landmark recognition while driving.

In the paper, two levels of integral representations, both in space and in time, are introduced in order to keep overall mission performance modular and easily tractable. Section 2 discusses the general spatial and temporal embedding schemes adopted in the 4-D approach. Section 3 is devoted to so-called 'local integrals', constituting mission elements from which the overall mission will be built up according to the actual situation encountered; here, a precise notion of a symbol and its different representations in different parts of the overall system will be given. These symbols will be used at the second level of integral representation for mission planning and monitoring as described in Section 4; they establish the transition to AI methods on a sound basis. Results will be discussed, including lane changes, crossroad recognition and turning off onto crossroads of unknown intersection angle and road width. Conclusions are given in Section 5.

2. SPATIAL AND TEMPORAL EMBEDDINGS

The performance level achieved with the 4-D approach and relatively small computing power on-board the vehicle has only been possible through an efficient parallel use of differential and integral representations which will be detailed here. Table 1 shows the chosen systematic subdivisions of the independent variables 3-D space (vertical) and time (horizontal).

All interaction with the real world happens at the point here and now (upper left field (1,1) of matrix). Inertial sensors pick up its accelerations, while an imaging sensor measures the intensity values over some spectral range at that point.

In the 4-D approach to dynamic vision a deliberate decision was made, to avoid taking temporal differences of image data because of the huge amount of data and of the noise problem involved. Time derivatives of the state variables of objects are computed by well-known observer techniques exploiting temporal (so-called 'dynamic') models of motion processes by prediction error feedback. This will be discussed in column 3 for local temporal integrals.

At each point in time, however, due to remote sensing with the speed of light, spatial neighborhoods may be explored. The immediate neighborhood yields spatial intensity gradients in the image, edge directions, edge curvatures and their change rates; all of this is subsumed under the term 'visual features'. They constitute spatial differentials as bottom-up information (matrix element (2,1)). These differentials may be integrated in somewhat larger environments in order to characterize pieces of the world by invariants. Rigid bodies, for example, are typical local integrals with invariant shapes in 3-D space; note that this shape invariance is lost through perspective projection in the image plane. Therefore, all spatial representations are done directly in 3-D space. Knowledge about the real world is mainly affixed to 3-D objects and their motion behavior, again in 3-D space and time. None the less, 2-D spatial regions in the image may also be considered to be local spatial integrals, characterized by some visual property.

The transition to larger environments or to global space may be performed at different space scales depending on the task at hand and the mission context; the state of an arrangement of objects in the mission context is called a 'situation'. Situations play an important role in decision taking since behaviors are defined in connection with mission elements to be performed, usually characterized by the situation.

Several space scales may be used in parallel at different organizational levels of the overall system. However, no fixed scheme of spatial scales is considered to be useful, independent of the task at hand.

The third column in Table 1 is the one containing the aspects most characteristic of the 4-D approach to dynamic vision. Especially, element (3,3) constitutes the central hub for dynamic scene understanding. As will be discussed in more detail below, it serves for temporal embedding of the understanding of motion processes in three functions:

1. single-step predictions for recursive state estimation for objects with known (or assumed) dynamics,
2. control computation for the own vehicle with the assignment of eigenvalues (dynamic behavioral

properties) including delay time compensation, and
3. multiple prediction steps for the generation of maneuver elements (both feedforward control and reference state time histories) for the own vehicle, and of likely trajectories of other objects (e.g. for collision avoidance).

This latter property is an input to the last entry in this column, characterizing the actual situation in the sense of an 'extended presence' as the basis for short-term decision taking.

This orientation towards physical objects (row 3) and temporal expectations (column 3) is the core of the 4-D approach. Maneuver elements of these objects of relatively short duration with well-defined initial and final conditions are the units for an easy transition from the control engineering methods at this level to the quasi-static 'artificial intelligence' (AI) methods usually preferred for handling knowledge-based overall mission performance (to the right and below, in Table 1).

At this level, also, the integration (sometimes called data fusion) of inertial (lower italic entries) and visual sensor data (upper entries in the relevant fields of Table 1) is performed. These data have nice complementary properties: inertial data are available immediately and at high rates; they may be integrated numerically to velocity components and position changes. Good dynamic properties are available at low costs; however, longer-term drift problems exist. On the other hand, results from image data, usually, become available only after some longer delay time; higher angular rates cause motion blur due to light intensity integration times in the sensor elements, and may destroy the image content. However, if the image sensors are short-term stabilized inertially, elements of the stationary environment can be recognized and long-term inertial stabilization is easily realized by visual feedback.

As opposed to (Albus, 1991) there is no hierarchy of sensory or actuatory elements prescribed in this approach. Also, the transition from local to global scales is left open for optimal adaptation to the special task at hand. Here, the central elements are objects and subjects; in (Dickmanns, 1989) subjects are defined as objects with the capability of control actuation and mode switching depending on their internal 'mental state', that is the totality of internal representations of the recursively estimated state relative to other objects which constitute the situation. Control time histories, feedback control laws, and their effects upon motion behavior are the key knowledge elements in the 4-D approach.

This knowledge is represented in symbolic form on the mission control level, allowing for task decomposition according to these behavioral capabilities in the planning phase. In the mission performance phase, switching between control modes is done by a monitoring process. For reliable mission performance under perturbations it has to be guaranteed that the radius of convergence of the ensuing control mode is larger than the outer bound of the final state errors of the previous mode at the actual time of switching.

Table 1. Different scale regions for representation in the 4-D approach

	point in time	temporal differentials	local temporal integrals	→	global temporal integrals
point in space	intensity value *accelerations* • *translatory* • *rotatory* } *'states'*	temporal intensity gradients	local intensity range, short term intensity distribution	multiple	long term intensity and color ranges, temporal distributions
spatial differentials	edge direction edge curvature spatial intensity gradients (higher moments) 'features'	optical flow feature motion *(incremental states)*	feature trajectories (short term)	time	long term feature trajectories
local spatial integrals	object shape segmented regions of an object (color, texture) *rotational speeds, angular positions*	object state incl. speeds, shape changes *incremental object states (vel., pos., angles)*	short term feature-, object trajectory integration of dynamical models *short term state ranges (transl., rot.) of objects*	→ scales	long term object trajectory *[long term history of objects (drift problems)]*
↓	multiple space scales			→	
global spatial integrals	arrangement of objects, mission space; actual situation (as seen 'at a glance')	actual situation change rate *relative object states*	extended presence, actual situation *short term development of situation*		long term development of situation mission performance *long term development of situation (drift problems)*
	based on visual measurements		*based on inertial measurements*		

This general scheme will be discussed below for the example of lane changing on a freeway, and for turning-off onto a crossroad. A block diagram is given as Fig. 4 below.

3. LOCAL INTEGRALS AND MISSION ELEMENTS

In road vehicle mission performance, large sections may be covered just by having a feedback control mode running, for instance 'lane keeping', in which the steering angle is adjusted to road curvature and lateral perturbations in such a way that the vehicle stays in the center of the lane (offsets may be added). A local integral in the mission context then is: distance driven equals speed times time (for constant speed); most mission performance is a sequence of such driving behavior. If a certain location has to be reached, the proper sequence of road segments leading to this location has to be chosen.

On freeways, all maneuvering and mission performance has to be achieved by proper lane selection, i.e. lane changes and lane following; therefore, mission performance is reduced to making lane changes at the appropriate point in time, or better, the appropriate location in the area of an intersection or a fork. For this reason, the mission element 'lane change' is also important for large-scale mission control, not just for passing slower traffic, but also for entering and leaving the freeway.

3.1 Lane changes

The capability to perform responsible lane change maneuvers involves more than just being able to initiate a steering control time history which results in a lateral offset of one lane width; it has to take the traffic situation around the vehicle into account, both to the side and behind the vehicle, in order not to hinder other traffic. This capability was developed in 1994 by adding a second set of bifocal cameras looking backwards; up to 5 other vehicles may be detected and tracked using state estimation relative to the vehicle's own body and lane, in both the forward and the rearward hemispheres simultaneously (Thomanek, et al., 1994). By 'mentally' tracking objects which leave the rearward cone of view at a certain excess speed relative to the vehicle's own speed, and checking their reappearance in the forward field of view, it can be deduced when the neighboring lane is free; this is true at least if the own vehicle is in the second lane from the side towards which the vehicle wants to change lane. If there is more than one lane on that side, lane changes of vehicles in these lanes cannot be tracked in the general case; this situation requires direct sensing. In the Daimler-Benz **VITA_II** twin vehicle, a set of six sideways-looking cameras, for stereo interpretation of the neighboring lane, have been added for the general case (Ulmer, 1994; Brauckmann, et al., 1994). If, in addition, no other car is approaching from behind at a high relative speed, a lane change is considered possible (Kujawski, 1995).

The actual lane change maneuver consists, basically, of a steering angle time history output according to some predefined structure with adaptable parameters. Three sequences seem practical: a) piecewise constant steering rates according to Figure 1a; b) a sinusoidal steering rate, (see Figure 1b), or c) a sinusoidal steering angle (Figure 1c). Version a) is the simplest one; however, it assumes infinite acceleration at steering turn onset (as does version c)) which is, of course, only approximately true; version b) is the most realistic and gentle one.

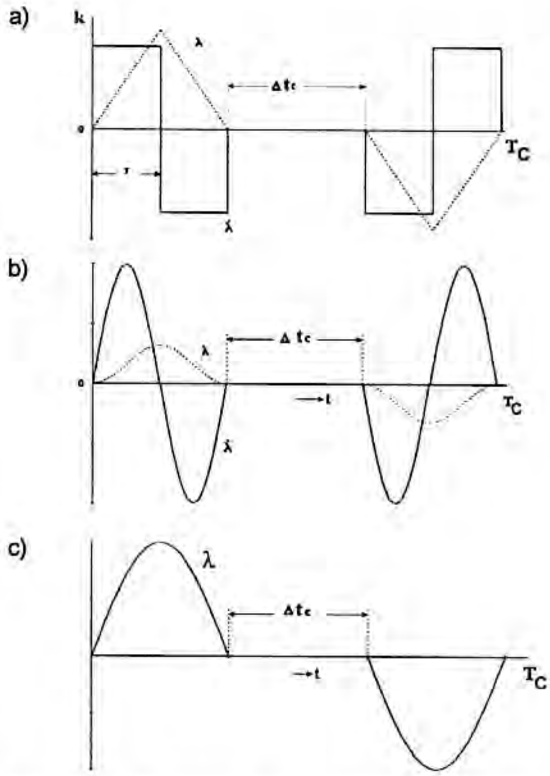

Figure 1. Alternative lane-change control feedforward time histories

For each control time history there follows a somewhat different vehicle trajectory. Version a) without the central part of the zero turn rate has been investigated in (Brüdigam, 1994); see Fig. 3 below.

Parameters are the magnitude of $\dot{\lambda}$, the duration of the control input T_c, the relative duration of the central null-input section Δt_C (in percent of T_c), and the total maneuver time for the state variables T_s.

Figure 2 shows some state variable time histories resulting from the control law of Fig. 1a for a speed of

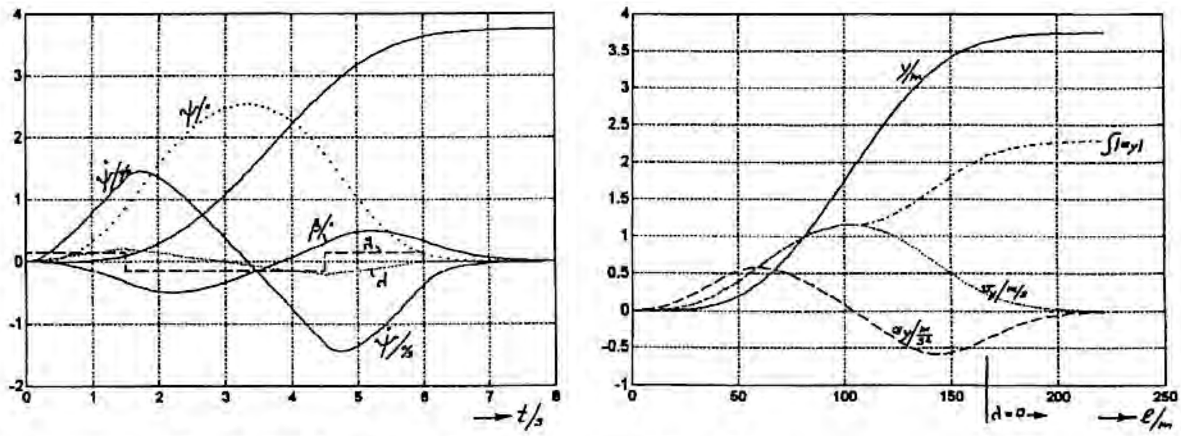

Fig. 2.1. V = 100 km/h; T_c = 6s; no central 0-input time span ($\Delta t_c = 0$)

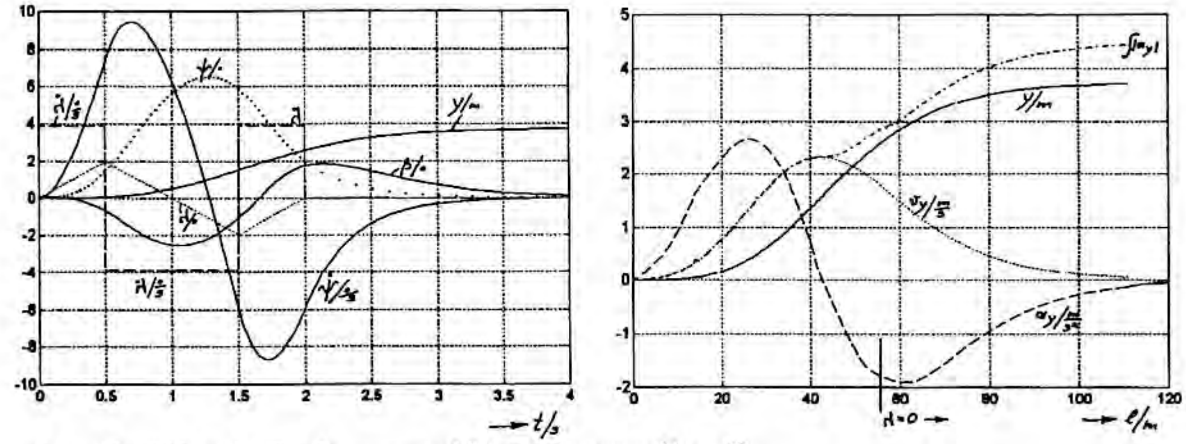

Fig. 2.2. V = 100 km/h; T_c = 2s; no central 0-input time span ($\Delta t_c = 0$)

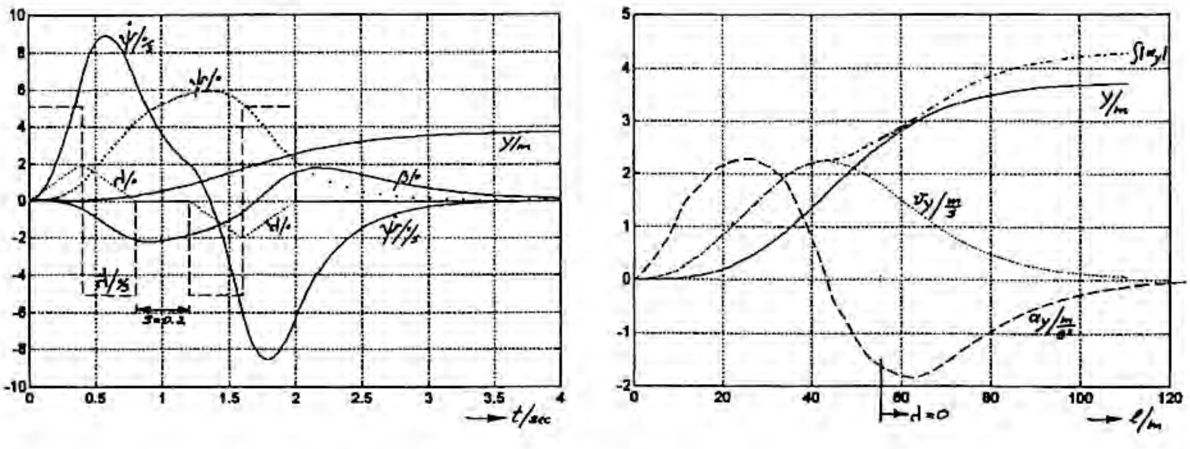

Fig. 2.3. V = 100 km/h; T_c = 2s; Δt_c = 20 % central 0-input time span

a) steer-(λ), slip-(β) and yaw angle (ψ) [in degrees] ($^\bullet$) = time derivative

b) lateral acceleration a_y [m/s^2] lateral speed v_y [m/s] lateral position y [m]

Figure 2. 'Lane change' control ($\dot{\lambda}$) and state variable time histories as parameter-dependent knowledge elements; parameters: driving speed V, control actuation time T_c

Table 2. Expectations for lane change maneuvers $\Delta y = 3.75m$ according to the 5th-order bicycle model with piecewise constant steer rates λ

	Column 1 Speed V km/h	2 T_c control maneuver time / s	3 λ deg/s	4 λ_{max} / deg	5 ψ_{max} / °	6 $\lvert\beta\rvert_{max}$ / °	7 $a_{y_{max}}$ / m/s^2	8 $v_{y_{max}}$ / m/s	9 $\int\lvert a_y\rvert$ / m/s	10 T_s state maneuver time / s	11 maneuver distance / s	remark
s = 0	40	6	0.9	1.4	6.4	0.16	0.7	1.2	2.4	6.5	75	
	40	4	3.1	3.1	9.6	0.36	1.5	1.8	3.6	4.5	54	
	40	2	24	12	18.5	1.7	5.2 $_{-4.8}$	3.2	6.3	2.7	34	
s = 0	100	6	0.16	0.22	2.5	0.5	0.6	1.2	2.3	7.9	220	fig 2.1
	100	4	0.5	0.5	3.7	0.95	1.1 $_{-1.05}$	1.6	3.2	6.0	168	
	100	2	3.9	2	6.5	2.6	2.7 $_{-1.9}$	2.35	4.7	4.4	125	fig 2.2
s = 0.2	100	6	0.18	0.23	2.2	0.5	0.6	1	2	7.9	~220	
	100	4	0.64	0.51	3.2	0.9	1 $_{-1}$	1.45	2.8	6	168	
	100	2	5.1	2	6	2.2	2.3 $_{-1.8}$	2.26	4.3	4.4	125	fig 2.3

100 km/h (27.8 m/s) and different parameters $T_c = 6$ and 2 sec, and $\Delta t_c = 0$ respectively 20 % (0.2). The parameters for a lane change of 3.75 m width, some maximal values of the maneuver, as well as total maneuver time T_s and distance are given in Table 2 for speeds of 40 and 100 km/h and some more parameter combinations; the trajectories of Fig. 2 may be found in rows 4, 6 and 9.

It is seen that both speed V and control maneuver time T_c do have a strong influence on the trajectories and their extremal values. The shorter the maneuver times (column 2), the larger the control inputs (column 3) have to be for the same lane width, and the higher are the extremal values of the state variables (columns 4 to 8) and the lateral acceleration (column 7) encountered. Column 5 gives the maximum heading change, column 6 the maximal absolute value of the slip angle, and column 8 the maximal lateral speed.

In column 9 the integral of the absolute value of the lateral acceleration as a measure of comfort is shown; in this simple maneuver this is, of course, twice the value of the maximal lateral speed. Column 10 displays the total time T_s for the state variables to settle to the steady state after the lane change maneuver; it can be seen from rows 6 and 9 that at higher speeds for dynamic maneuvers (small T_c) this total time may be more than twice the feedforward control input time. Figures 2.2b and 2.3b show that the maximal negative accelerations occur after finishing the feedforward control input at zero steer angle when also the slip angle attains its maximum. Comparing rows 3, 6 and 9 in column 7 it is recognized that peak lateral acceleration decreases strongly with speed and slightly with a central zero steer angle control arc dividing the lane change maneuver into two impulse-like maneuver elements. Note that, because of the eigendynamics of the vehicle, the positive and negative acceleration peaks are different for the same control input for these highly dynamic maneuvers; for larger separation times between these maneuver elements they become equal and opposite, of course.

All these different maneuvers are subsumed under the symbol 'lane change'; it achieves its specific meaning depending on the situation in which it is invoked. Speed and lane width are taken from the actual measurements (tachometer or vision) while the selected control maneuver time T_c is specified by the calling module 'behavior decision'; this time, however, is not equal to the actual state transition time T_s. From these examples it should have become clear that interfacing the control engineering methods with AI methods has to be done with care, taking dynamic and situational aspects into account.

If perturbations are to be expected, the state variable time histories that have been computed serve as the command input to a superimposed feedback loop counteracting the perturbations.

Figure 3 shows control and state time histories of a slow real lane change maneuver of the new autonomous vehicle **VaMP** (see (Maurer, et al., 1994)) containing the superimposed feedback mode.

It is seen that appreciable deviations from the ideal maneuver occur in practical situations with continuous corrective control action.

This generic feedforward control time history with superimposed feedback control may be abbreviated by a symbol, say 'lane change (step input)'; the higher levels in the system do not need to know how this symbol is translated into physical control outputs. It suffices if they know the net result at the end, and maybe some significant extrema and their times of

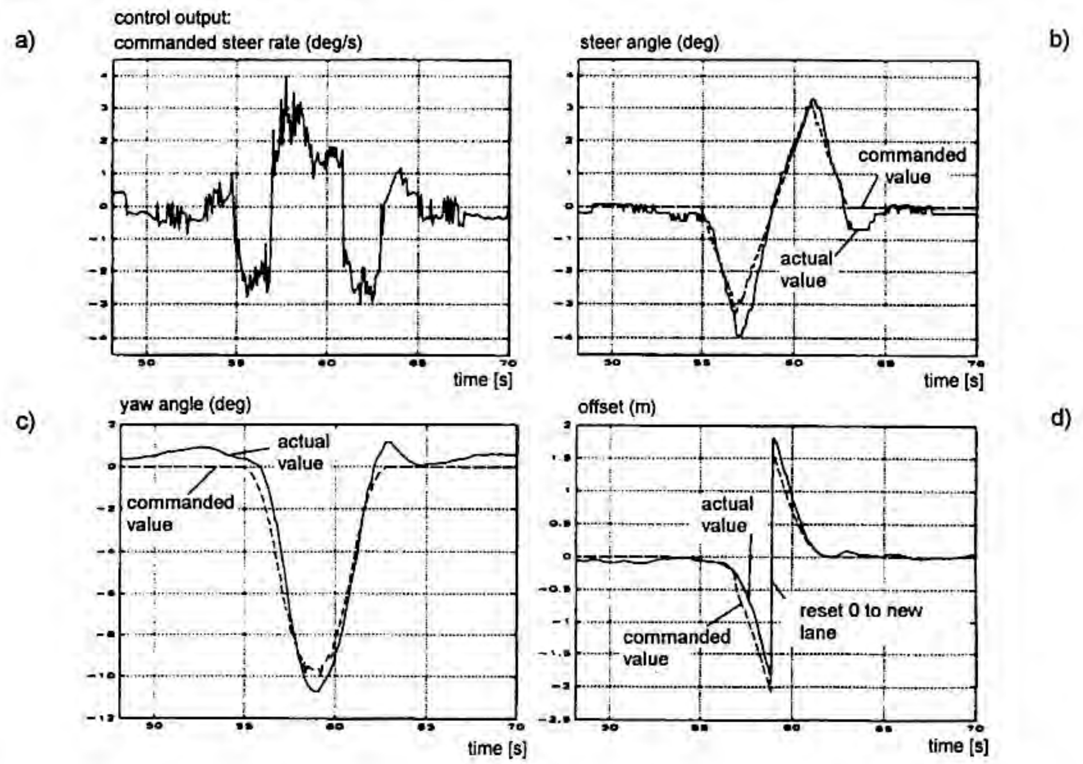

Figure 3. Time history of steer rate (a), steer angle (b), yaw angle (c) and lateral offset (d) commanded for a lane change maneuver; superimposed feedforward and feedback control (after (Brüdigam, 1994)).

occurrence in between, for monitoring the maneuver being performed; these expected values give confidence that the goal of the maneuver will be achieved, or they may be used for triggering corrective actions.

On the lower behavior realisation level this knowledge about an ideal trajectory, resulting from a feedforward control input time history, will be used in the case of perturbations for deriving superimposed corrective ac-

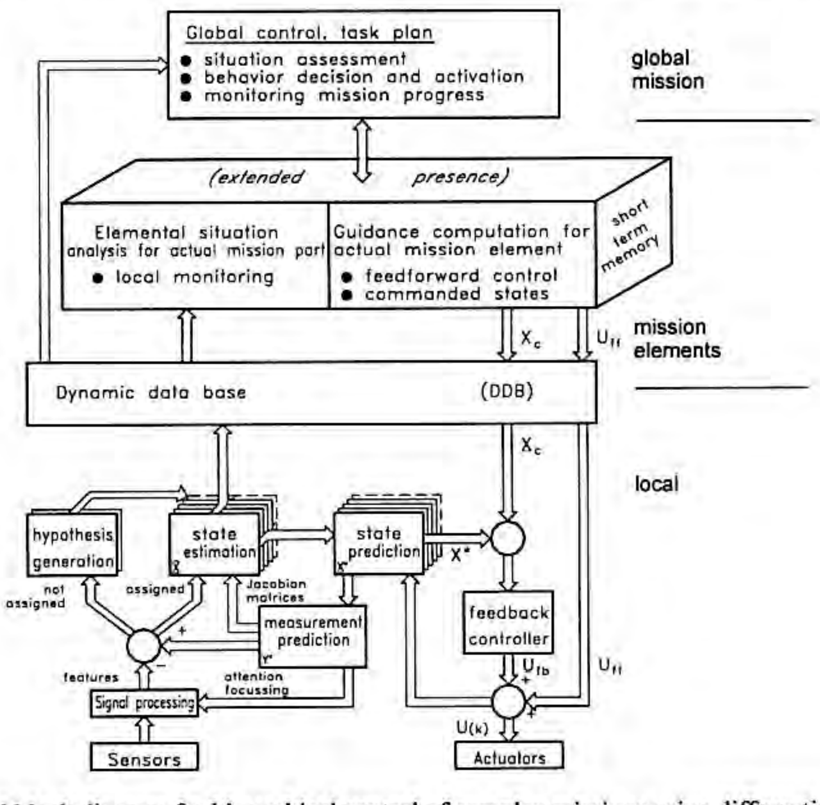

Figure 4. General block diagram for hierarchical control of complex missions using differential and integral representations in parallel in both space and time

tion in a reflex-like manner: besides the feedforward control component, an additive feedback component is computed from the difference between the expected value according to the analytically or numerically computed ideal solution and the measured value (see Fig. 4). By this means it is ensured that the error at the end of this maneuver element is small enough that the feedback law of the ensuing mission element (lane keeping in this case) is capable of correcting the remaining errors.

3.2 Turn-offs

The second most important maneuver element for driving on general roads is recognition of proper crossroads and turning-off onto them. Making a turn into a crossroad on the normal driving side (to the right in continental Europe and the Americas, to the left in the UK, etc.) is the easier of the two possibilities; crossing oncoming traffic lanes requires the traffic situation on these lanes to be checked too. The maneuvering capability developed for turn-offs is currently confined to the case where there is no interference with any other vehicle or obstacle, either on the own or on the crossroad.

It is assumed that the higher levels have been able to determine from odometry (or a GPS reading) that the next upcoming crossroad (with certain visual features) will be the one to turn onto; the precise location, width and relative orientation, however, are unknown (see Fig. 5). These have to be determined while approaching the crossroad; therefore, speed will be reduced in order to make more processing time available per distance travelled.

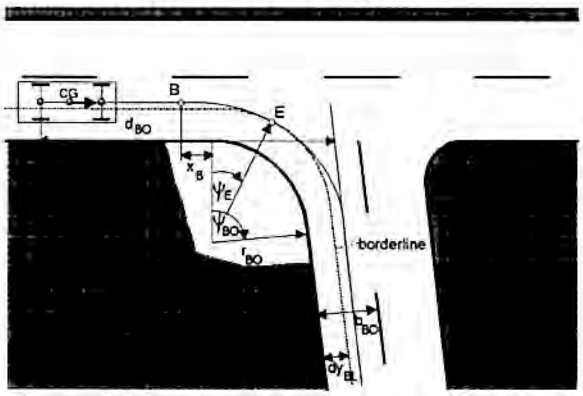

Figure 5. Turn-off maneuver with active vision

An additional crossroad-detection window will be positioned to the side of the road being driven along, and a feature search will be started. Both edge- and area-based features are sought, the latter being more robust under the aspect conditions initially given. Edge features are generally extracted with ternary masks (templates) as shown in Fig. 6.

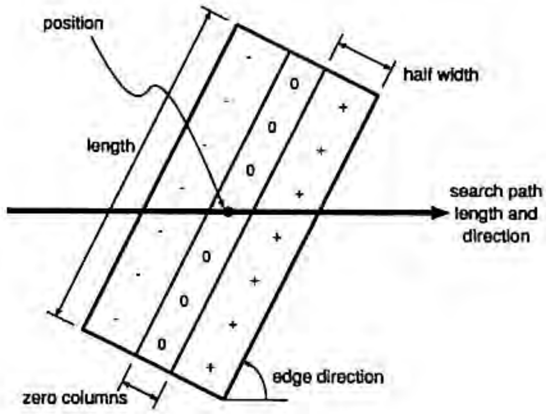

Figure 6. Masks used for edge detection (generic set)

The mask parameters are intelligently controlled by the interpretation process; they vary with time and distance of interpretation.

Area-based features are grey values, color components or texture measures; they are computed in a 'one-dimensional pyramid' called the 'triangle', erected over image slices, the width and orientation of which are again intelligently controlled by the interpretation process.

When a set of features indicative of a crossroad candidate has been detected in several consecutive evaluation cycles of 80 ms, a systematic search with hypothesized crossroad parameters (like width and intersection angle, usually assumed to be 90°) is started, and the viewing direction starts turning into the crossroad while approaching it; this may be thought of as a long stick being pushed in front of the vehicle with the tip following the center of the lane to be turned into: while the vehicle is still moving straight ahead, the vehicle's eye turns to almost a right angle relative to the car body. This improves the aspect conditions for precisely determining the parameters of the crossroad; at a triggering point depending on the parameters found, a steering rate feedforward control program is started which should lead to a trajectory for negotiating the curve smoothly. Here also, superimposed feedback components take care of perturbations and the effects of imprecise modeling. Since the viewing direction is fixed to the crossroad, it hardly turns relative to the spine of this road; however, the vehicle now turns underneath the camera. Figure 7 from (Müller and Baten, 1995) shows the time histories of the most important variables involved. At zero seconds the rapid turning of the viewing direction starts. At about 13 seconds the steering angle ramp starts increasing the vehicle heading; the camera heading relative to the

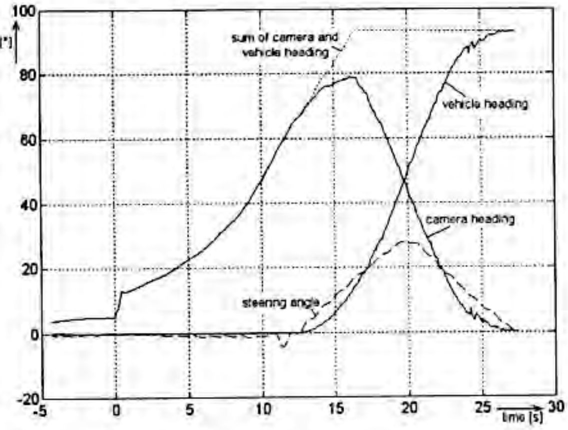

Figure 7. Maneuver element 'turn-off onto cross-road'; (from (Müller and Baten, 1995))

vehicle body achieves its maximum value of 79° at t = 17s. While the sum of camera and vehicle heading angles continues to increase to its final value of 93° in the case shown, the camera heading angle relative to the vehicle body is turned back and reaches zero when the vehicle body is aligned to the new road spine (at about 27s); more details on this maneuver may be found in the reference; space does not allow further discussion here.

It is seen that the mission element 'turn-off at the next crossroad (right or left)' is rather involved, requiring activity sequences both in viewing direction and in feature-extraction control, as well as in steering-control outputs which have to be coordinated relative to each other, including some feedback loops for fixing the viewing direction; all these activities may be symbolized on a higher level of representation by the symbol 'make turn (right/left)'.

As in the case of lane changes, a complex control output pattern ranging over an extended period of time and performing a transition in the vehicle's state from its initiation at trigger time t_t (relative zero) to its relative final time T_s is represented on the higher level quasi-statically just as an abstract transition between time points t_t and $t_t + T_s$; on the lower implementation level it is represented by procedural codes based on differential models, possibly combined with table look-ups and even with feedback control components for dealing with unforseeable perturbations (see Fig. 4 again). As long as the control laws are able to transfer the vehicle, despite perturbations, into a state from which a new behavioral capability can be started, this type of sequencing of maneuver elements is robust and well suited to dealing with partially unknown environments. It makes mission performance modular and flexible.

A similar local maneuver element (behavioral capability) has to be available for handling forks in the road. By using these elements in the proper sequence and according to the situation encountered, the mission goal can be achieved by rather abstract planning on the higher levels.

4. MISSION PLANNING AND MONITORING

The overall task to be performed has to be divided into a sequence of subtasks for which capabilities are available in the system; at the time of transition between these subtasks, convergence from non-nominal states has to be guaranteed by the new control mode entered, in order to ensure mission success. By this approach, much of the planning task is reduced to behavioral capabilities and knowledge about these capabilities on the higher system levels; the transition regions between behavioral modes are usually the most critical ones.

Everybody knows from their own experience that taking a wrong turn endangers, or at least defers, mission success; according to the information one needs during particular parts of the mission, therefore, travel maps are very often topological ones, with just a few words for possibly large distances to be traveled (like take freeway xy from entry A to exit B), and rather detailed information about 'islands of decision'. At these islands a perspective view may be given with the most remarkable visual features emphasized, in a more qualitative or even quantitative way; these visual 'landmarks' serve for recognizing the decision island. Once this has been achieved, the rest of this part of the mission may be reduced to a sequence of local behavioral activities like taking a turn or a fork, according to the map information provided for the mission. Thus, the overall integration of the mission is the activation of a list of maneuver elements at correctly recognized landmarks; for human navigation in more densely populated areas, these landmarks are characterized by navigational traffic signs recognizable by certain color codes. In (Hock, 1994), because of the lack of computing power for full traffic-sign recognition at the moment, these landmarks are rectangular signs with simple black and white geometric patterns; the precise environmental parameters are recognized by active viewing direction control using a bifocal vision system while the crossroad was approached.

The tests have been performed with the **VaMoRs** test vehicle (see Fig. 8) on a closed-down airport next to the authors' university (Dickmanns, et al., 1994).

At the moment, the capability to start focusing attention by using imprecise GPS data in combination with a coarse map is being developed; both flexible perceptual and behavioral capabilities make up for the imprecision in both knowledge about the environment and measurement accuracies. Local visual feedback and adaptation to the actual environmental parameters are considered vital for flexible mission performance in a loosely

Figure 8. UniBwM's **VaMoRs** test vehicle

defined task context; these capabilities make an autonomous system a pleasant and easy-to-handle partner for achieving mission goals efficiently.

5. CONCLUSIONS

In the 4-D approach to intelligent autonomous vehicles, flexible perceptual and behavioral capabilities based on spatio-temporal models make up for imprecision, both in knowledge about the environment and in measurements. Conventional control engineering methods like (situation-dependent) feedback control laws and adaptable feedforward control time histories, with proper switching between modes depending on the situation encountered, are the means by which these performance capabilities have been achieved.

Mission elements are represented at least twice in different parts of the system: in the vehicle control processors the time sequence of control outputs has to be generated by parameterized procedural methods. This implements the symbolic representation on the higher mission-planning level where a symbol for the behavioral mode, together with the proper parameters and the transition effects of the entire maneuver element over its time of duration, is sufficient. Since expectations of state variable time histories resulting from the control outputs may be derived from an ideal model, superimposed feedback corrections of prediction errors may decrease the effect of perturbations on the actual trajectory as compared to the ideal one.

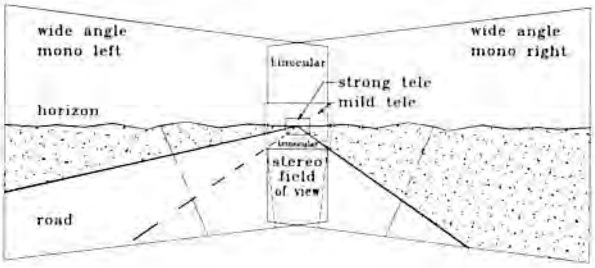

Figure 9. Fields of view of the proposed complex road-vehicle eye

Entire missions are pieced together as sequences of subtasks which are initially derived off-line from abstract mission planning, taking the perceptual and behavioral capabilities of the autonomous system into account. Ultimately, all of this will be performed fully automatically.

Experience has shown that for robust mission performance by this method the visual perception capabilities have to be further improved: high resolution further away is required for more versatile landmark recognition; for turning off and precise maneuvering relative to obstacles nearby, both a wider field of view and a capability for stereo vision will need to be available. Figure 9 from (Dickmanns, 1995) shows the visual fields of view of a complex road vehicle eye presently under development at UniBwM, with 4 CCD sensors which will allow high-performance visual perception and corresponding maneuver control.

REFERENCES

Albus, J. (1991). Outline for a Theory of Intelligence. *IEEE Trans. Systems, Man, and Cybernetics*, Vol. 21, No. 3, May/June.

Brauckmann, M.E., Chr. Goerick, J. Gro and T. Zielke (1994). Towards All Around Automatic Visual Obstacle Sensing for Cars. *Proc. 'Intelligent Vehicles'*, Paris, Oct., pp 79-84.

Brooks, R.A. (1986). A Robust Layered Control System for a Mobil Robot. *IEEE J. of Robotics and Automation*, RA-2, April, pp 14-23.

Brüdigam, C. (1994). Intelligente Fahrmanöver sehender autonomer Fahrzeuge in autobahnähnlicher Umgebung. Dissertation, Universität der Bundeswehr München, Fakultät für LRT.

Dickmanns, E.D. and A. Zapp (1987). Autonomous High Speed Road Vehicle Guidance by Computer Vision. *10th IFAC World Congress Munich*, Preprint **4**, pp 232-237.

Dickmanns, E.D. (1989). Subject-Object Discrimination in 4-D Dynamic Scene Interpretation by Machine Vision. *Proc. IEEE-Workshop on Visual Motion*, Newport Beach, pp 298-304.

Dickmanns, E.D. and T. Christians (1989). Relative 3-D State Estimation for Autonomous Visual Guidance of Road Vehicles. *Proc. Intelligent Autonomous Systems-2*, Amsterdam, Dec.

Dickmanns, E.D., R. Behringer, D. Dickmanns, T. Hildebrandt, M. Maurer, F. Thomanek and J. Schiehlen (1994). The Seeing Passenger Car 'VaMoRs-P'. *Proc. 'Intelligent Vehicles'*, Paris, Oct.

Dickmanns, E.D. (1995). Road Vehicle Eyes for High Precision Navigation. *Proc. Symp. on 'High Precision Navigation'*, Stuttgart, April.

Hock, Chr. (1991). Landmark Navigation with ATHENE. 5. *Int. Conf. on Advanced Robotics*, Pisa, Italy, June.

Hock, Chr. (1994). Wissensbasierte Fahrzeugführung mit Landmarken für autonome Roboter. Dissertation, Universität der Bundeswehr München, Fakultät für LRT.

Klass, P.J. (1985). DARPA Envisions New Generation of Machine Intelligence. *Aviation Week & Space Technology*, April, pp 47-54.

Kujawski, C. (1995). Deciding the Behaviour of an Autonomous Road Vehicle Complex in Traffic Situations. *2nd IFAC Conf. on Intelligent Autonomous Vehicles-95*, Helsinki University of Technology, Otaniemi (Finland), June.

Maurer, M., R. Behringer, D. Dickmanns, T. Hildebrandt, J. Schiehlen and E.D. Dickmanns (1994). VaMoRs-P An Advanced Platform for Visual Autonomous Road Vehicle Guidance. *SPIE Conference 'Mobile Robots IX'*, Oct. 31 - Nov. 4.

Meissner, H.G. (1982). Steuerung dynamischer Systeme aufgrund bildhafter Informationen. Dissertation, Universität der Bundeswehr München, Fakultät für LRT.

Müller, N. and S. Baten (1995). Image Processing Based Navigation with an Autonomous Car. *Int. Conf. on Intelligent Autonomous Systems* (IAS-4), Karlsruhe, March.

Thomanek, F., E.D. Dickmanns and D. Dickmanns (1994). Multiple Object Recognition and Scene Interpretation for Autonomous Road Vehicle Guidance. *Proc. 'Intelligent Vehicles'*, Paris, Oct.

Ulmer, B. (1994). VITA II - Active collision avoidance in real traffic. *Proc. 'Intelligent Vehicles'*, Paris, Oct.