Appendix A
Contributions to Ontology for Ground Vehicles

A.1 General Environmental Conditions

A.1.1. Distribution of ground on Earth to drive on (global map)

Continents and Islands on the globe
- Geodetic reference system, databases
- Specially prepared roadways: road maps
- Cross-country driving, types of ground
  - Geometric description (3-D)
  - Support qualities for tires and tracks
- Ferries linking continents and islands

National Traffic Rules and Regulations

Global navigation system availability

A.1.2. Lighting conditions as a function of time

Natural lighting by sun (and moon)
- Sun angle relative to the ground for a given location and time
- Moon angle relative to the ground for a given location and time

Headlights of vehicles
Lights for signaling intentions/special conditions
Urban lighting conditions
Special lights at construction sites (incl. flashs)
Blinking blue lights

A.1.3 Weather conditions

Temperatures (Effects on friction of tires)
Winds
Bright sunshine/Fully overcast/Partially cloudy
Rain/Hail/Snow
Fog (visibility ranges)
Combinations of items above
Road surface conditions (weather dependent)
Dry/Wet/Slush/Snow (thin, heavy, deep tracks) /Ice
Leaf cover (dry – wet)/Dirt cover (partial – full)

A.2 Roadways

A.2.1.Freeways, Motorways, Autobahnen etc.

Defining parameters, lane markings
Limited access parameters
Behavioral rules for specific vehicle types
Traffic and navigation signs
Special environmental conditions

A.2.2. Highways (State-), high-speed roads

Defining parameters, lane markings (like above)

A.2.3. Ordinary state roads (two-way traffic) (like above)
A.2.4. Unmarked country roads (sealed)
A.2.5. Unsealed roads
A.2.6. Tracks
A.2.7. Infrastructure along roadways

Line markers on the ground, Parking strip, Arrows,
Pedestrian crossings
Road shoulder, Guide rails
Regular poles (reflecting, ~1 m high) and markers for snow conditions

A.3 Vehicles

(as objects without driver/autonomous system; wheeled vehicles, vehicles with tracks, mixed wheels and tracks)

A.3.1. Wheeled vehicles

Bicycle: Motorbike, Scooter;
Bicycle without a motor: Different sizes for grown-ups and children
Tricycle
Multiple (even) number of wheels
Cars, Vans/microbuses, Pickups/Sports utility vehicles, Trucks, Buses, Recreation vehicles, Tractors, Trailers

A.3.2. Vehicles with tracks
A.3.3. Vehicles with mixed tracks and wheels

A.4 Form, Appearance, and Function of Vehicles

(shown here for cars as one example; similar for all classes of vehicles)

A.4.1. Geometric size and 3-D shape (generic with parameters)
A.4.2. Subpart hierarchy

Lower body, Wheels, Upper body part, Windshields (front and rear)
Doors (side and rear), Motor hood, Lighting groups (front and rear)
Outside mirrors

A.4.3. Variability over time, shape boundaries (aspect conditions)
A.4.4. Photometric appearance (function of aspect and lighting conditions)

Edges and shading, Color, Texture

A.4.5. Functionality (performance with human or autonomous driver)

Factors determining size and shape
Performance parameters (as in test reports of automotive journals; engine power, power train)
Controls available [throttle, brakes, steering (*e.g.*, “Ackermann”)]
Tank size and maximum range
Range of capabilities for standard locomotion:
Acceleration from standstill
Moving into lane with flowing traffic
Lane keeping (accuracy)
Observing traffic regulations (max. speed, passing interdiction)

Distance keeping from vehicle ahead
(standard, average values, fluctuations)
Lane changing [range of maneuver times as *f*(speed)]
Overtaking behavior [safety margins as *f*(speed)]
Braking behavior (moderate, reasonably early onset)
Proper setting of turn lights before start of maneuver
Turning off onto crossroad
Entering and leaving a circle
Handling of road forks
Observing right of way at intersections
Negotiating “hair-pin” curves (switchbacks)
Proper reaction to static obstacle detected in your lane
Proper reaction to animals detected on or near the driveway
Emergency stops
Parking alongside the road
Parking in bay
U-turns
Safety features (ABS, ESP …)
Self-check capabilities
Tire pressure
Engine performance (a few easy standard tests like “gas pulses”)
Brake performance

A.4.6. Visually observable behaviors of others

(driven by a human or autonomously)

Standard behavioral modes (like list of capabilities above)

Unusual behavioral modes

Reckless entrance into your lane from parking position or neighboring lane at much lower speed
Oscillations over entire lane width (even passing lane markings)
Unusually slow speeds with no noticeable external reason
Disregarding traffic regulations [max. speed (average amount), passing interdiction, traffic lights]
Very short distance to vehicle ahead
Hectic lane change behavior, high acceleration levels (very short maneuver times, large vehicle pitch and bank angles, “slalom” driving)
Overtaking behavior (daring, frequent attempts, questionable safety margins, cutting into your lane at short distance)
Braking behavior (sudden and harsh?)
Start of lateral maneuvers before or without proper setting of turn lights.
Speed not adapted to actual environmental conditions (uncertainties and likely fluctuations taken into account)
Disregarding right of way at intersections.
Pedestrians disregarding standard traffic regulations
Bicyclists disregarding standard traffic regulations

Recognizing unusual behavior of other traffic participants due to unexpected or sudden malfunctions (perturbations).
Reaction to animals on the driveway (f(type of animal))
Other vehicles slipping due to local environmental conditions (like ice)

A.4.7. Perceptual capabilities

A.4.8 .Planning and decision making capabilities

A.5 Form, Appearance, and Function of Humans

(Similar structure as above for cars plus modes of locomotion)

A.6 Form, Appearance, and Likely Behavior of Animals

(relevant in road traffic: Four-legged, birds, snakes)

A.7 General Terms for Acting "Subjects" in Traffic

Subjects: Contrary to "objects" (proper), having passive bodies and no capability of self-controlled acting, "subjects" are defined as objects with the capability of sensing and self-decided control actuation. Between sensing and control actuation, there may be rather simple or quite complicated data processing available taking stored data up to large knowledge bases into account. From a vehicle guidance point of view, both human drivers and autonomous perception and control systems are subsumed under this term. It designates a superclass encompassing all living beings and corresponding technical systems (*e.g.*, robots) as members.

These systems can be characterized by their type of equipment and performance levels achieved in different categories. Table 3.1 shows an example for road vehicles.

The capabilities in the shaded last three rows are barely available in today's experimental intelligent road vehicles. Most of the terms are used for humans in common language. The terms "behavior" and "learning" should be defined more precisely since they are used with different meanings in different professional areas (*e.g.*, in biology, psychology, artificial intelligence, engineering).

Behavior (as proposed here) is an all-encompassing class term subsuming any kind and type of 'action over time' by subjects.

Action means using any kind of control variable available to the subject, leading to changes in the state variables of the problem domain.

State variables are the set of variables allowing decoupling future developments of a dynamic system from the past (all the history of the system with respect to body motion is stored in the present state); state variables cannot be changed at one moment. (Note two things: (1) This is quite the opposite of the definition of "state" in computer science; (2) accelerations are in general not (direct) state variables in this systems-dynamics sense since changes in control variables will affect them directly.)

Control variables are the leverage points for influencing the future development of dynamic systems. In general, there are two components of control activation involved in intelligent systems. If a payoff function is to be optimized by a "*maneuver*", previous experience will have shown that certain control time histories perform better than others. It is essential knowledge for good or even optimal control of dynamic systems, to know in which situations to perform what type of maneuver with which set of parameters; usually, the maneuver is defined by certain time histories of (coordinated) control input. The unperturbed trajectory corresponding to this nominal feed-forward control is also known, either stored or computed in parallel by numerical integration of the dynamic model exploiting the given initial conditions and the nominal control input. If perturbations occur, another important knowledge component is knowing how to link additional control inputs to the deviations from the nominal (optimal) trajectory to counteract the perturbations effectively. This has led to the classes of feed-forward and feedback control in systems dynamics and control engineering:

Feed-forward control components $\underline{\boldsymbol{U}}_{ff}$ are derived from a deeper understanding of the process controlled and the maneuver to be performed. They are part of the knowledge base of autonomous dynamic systems (derived from systems engineering and optimal control theory). They are stored in generic form for classes of '*maneuvers*'. Actual application is triggered from an instance for behavior decision and implemented by an embedded processor close to the actuator, taking the parameters recommended and the actual initial and desired final conditions (states) into account.

Feedback control components $\underline{\boldsymbol{u}}_{fb}$ link actual (additional) control output to system state or (easily measurable) output variables to force the trajectory toward the desired one despite perturbations or poor models underlying step 1. The technical field of 'control engineering' has developed a host of methods also for automotive applications. For linear (linearized) systems, linking the control output to the entire set of state variables allows specifying the "eigenmodes" '*at will*' (in the range of validity of the linear models). In output feedback, adding components proportional to the derivative (D) and/or integral (I) of the signal allows improving speed of response (PD) and long-term accuracy (PI, PID).

Combined feed-forward and feedback control: For counteracting at least small perturbations during maneuvers, an additional feedback control component $\underline{\boldsymbol{u}}_{fb}$ may be superimposed on the feed-forward one ($\underline{\boldsymbol{U}}_{ff}$) yielding a robust implementation of maneuvers.

Longitudinal control: In relatively simple, but very often sufficiently precise models of vehicle dynamics, a set of state variables affected by throttle and (homogeneous) braking actions with all wheels forms an (almost) isolated subsystem. It consists of the translational degrees of freedom in the vertical plane containing the plane of symmetry of the vehicle and the rotational motion in pitch, normal to this plane. The effects of gravity on sloping surfaces and the resulting performance limits are included.

Lateral control: Lateral translation (y direction), rotations around the vertical (z) and the longitudinal (x) axes form the lateral degrees of freedom, controlled essentially by the steer angle. Lateral motion of larger amplitude does have an influence also on longitudinal forces and pitching moment.

Maneuvers are stereotypical control output time histories (feed-forward control) known to transform (in the nominal case) the initial system state $\underline{\mathbf{x}}(t_0)$ into a final one $\underline{\mathbf{x}}(t_f)$ in a given time (range) with boundary conditions (limits) on state variables observed. Certain ranges of perturbations during the maneuver can be counteracted by superimposed feedback control.

Maneuvers may be triggered by higher level decisions for implementing strategic '*mission elements*' (*e.g.*, turning off onto a crossroad) or in the context of a behavioral mission element running, due to the actual *situation* encountered (*e.g.*, lane change for passing slower traffic or an evasive maneuver with respect to a static obstacle during 'roadrunning').

Table 3.3 *gives a collection of road vehicle behavioral capabilities realized by feed-forward (left column) and feedback control (right column).*

Mission elements are those parts of an entire mission that can be performed with the same subset of behavioral capabilities and parameters. Note that mission elements are defined by sets of compatible behavioral capabilities of the subject *actually performing* the mission.

Situation is the collection of environmental and all other facts that have an influence on making proper (if possible 'optimal') behavior decisions in the mission context. This also includes the state within a maneuver being performed (percentage of total maneuver performed, actual dynamic loads, *etc*.) and all safety aspects.

General comment:

Dimension: There are only four dimensions in our (mesoscale) physical world: Three space components and time. Rotational rates and velocities are components of the physical state, due to the nature of mechanical motion described by second-order differential equations (Newton's law). These velocity components are additional degrees of freedom (d.o.f.), but not dimensions as claimed in some recent publications. Recursive estimation with physically meaningful models delivers these variables together with the pose variables.

Dimensions from discretization: In search problems it is a habit to call the possible states of a variable the dimension of the search space; this has nothing to do with physical dimensions.

Appendix B
Lateral Dynamics

B.1 Transition Matrix for Fourth-Order Lateral Dynamics

The linear process model for lateral road vehicle guidance derived in Chapters 3 and 7 (see Table 9.1) can be written as a seventh order system in analogue form [Mysliwetz 1990]:

$$\dot{x}(t) = Fx + g'u + v'(t) \qquad \text{(Equation 3.6 with one control variable)} \qquad \text{(B.1)}$$

$$\begin{pmatrix} \dot{\lambda} \\ \dot{\beta} \\ \dot{\psi}_{rel} \\ \dot{y}_V \\ \hline \dot{C}_{0hm} \\ \dot{C}_{1hm} \\ \dot{C}_{1h} \end{pmatrix} = \left(\begin{array}{cccc|ccc} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ f_{12} & -1/T_\beta & 0 & 0 & 0 & 0 & 0 \\ V/a & 0 & 0 & 0 & -V & 0 & 0 \\ 0 & V & V & 0 & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 & V & 0 \\ 0 & 0 & 0 & 0 & 0 & -3\cdot V/L & 3\cdot V/L \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{array}\right) \begin{pmatrix} \lambda \\ \beta \\ \psi_{rel} \\ y_V \\ \hline C_{0hm} \\ C_{1hm} \\ C_{1h} \end{pmatrix} + \begin{pmatrix} k_\lambda \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \cdot u(t) + \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ n_{C_{1h}} \end{pmatrix}$$

with $f_{12} = 1/(2T_\beta) - V/a$; $\quad T_\beta = V/\,k_{ltf}$; $\quad$ Equation 3.30.

With T as cycle time for sampling (video frequency), the Laplace transform for the transition matrix is (see, *e.g.*, [Kailath 1980]):

$$A(T) = L^{-1}\{(sI - F)^{-1}\,. \qquad \text{(B.2)}$$

For the discrete input gain vector g, one obtains from F and g'

$$g = \int_0^T A(\tau) g' d\tau\,. \qquad \text{(B.3)}$$

The noise term also has to be adjusted properly in correspondence with T. The resulting difference equation is B.4. The matrix A and the input gain vector g have the entries given below (note that g has many more entries than g'; this is due to the buildup of state components from constant control input over one cycle!):

$$x(k+1) = A \cdot x(k) + g \cdot u(k) + v(k)\,. \qquad \text{(B.4)}$$

$$A = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 & 0 & 0 \\ a_{31} & 0 & 1 & a_{34} & a_{35} & a_{36} & a_{37} \\ a_{41} & a_{42} & a_{43} & 1 & a_{45} & a_{46} & a_{47} \\ 0 & 0 & 0 & 0 & 1 & a_{56} & a_{57} \\ 0 & 0 & 0 & 0 & 0 & a_{66} & a_{67} \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \quad \text{and} \quad g = \begin{pmatrix} g_1 \\ g_2 \\ g_3 \\ g_4 \\ 0 \\ 0 \\ 0 \end{pmatrix}. \qquad \text{(a)}$$

With the following abbreviations:

$$c_F = V/a; \qquad a_F = -2\mathrm{k}_{\mathrm{ltf}}/V;$$
$$b_F = -\mathrm{k}_{\mathrm{ltf}}/V + c_F; \qquad a_c = -3V/L;$$

the non-vanishing elements a_{ij} of the transition matrix are

$$a_{21} = b_F/a_F \cdot (e^{a_F T} - 1); \qquad a_{22} = e^{a_F T}$$
$$a_{31} = c_F T; \quad a_{35} = -VT; \quad a_{36} = V^2/a_c^2 \cdot (a_c T + 1 - e^{a_c T});$$
$$a_{37} = -V^2[(1 - e^{a_c T})/a_c^2 + T/a_c + T/2];$$
$$a_{41} = (b_F V/a_F) \cdot [(e^{a_F T} - 1)/a_F - T] + c_F V T^2/2;$$
$$a_{42} = (e^{a_F T} - 1)V/a_F; \qquad a_{43} = VT; \qquad a_{45} = -V^2 T^2/2;$$
$$a_{46} = V^3[(1 - e^{a_c T})/a_c^2 + T/a_c + T/2]/a_c;$$
$$a_{47} = -V^3[-(1 - e^{a_c T})/a_c^3 + T/a_c^2 + T/(2a_c) + T^3/6];$$
$$a_{56} = -V(1 - e^{a_c T})/a_c; \qquad a_{57} = V(a_c T + 1 - e^{a_c T})/a_c;$$
$$a_{66} = e^{a_c T}; \qquad a_{67} = 1 - e^{a_c T}.$$

The entries in the input gain vector are

$$g_1 = T; \quad g_2 = b_F/a_F \cdot \{(e^{a_F T} - 1)/a_F - T\}; \quad g_3 = c_F T^2/2;$$
$$g_4 = -b_F V/a_F^2 \cdot [T + a_F T^2/2 - (e^{a_F T} - 1)/a_F] - c_F V T^3/6.$$

The rows in matrix A are given by the first index; this corresponds to the sequential innovation scheme in square root filtering using row vectors of *A*. Note that out of the 49 elements of *A*, 26 are zero (53%); explicit use of this structure can help making vector multiplication very economical: for rows 1 and 7 (first and last), the result has the same value as the multiplicand. For row index 2, multiplication of elements can stop at this row index 2, while for indices 5 and 6, starting multiplication at these indices is sufficient. Efficiently coded, many multiplications may be saved in this inner loop that is always running. Since several multiplications with these vectors occur in recursive computation of the expected error covariance (step 7.2 in Table 6.1), being efficient here really pays off in real-time vision.

B.2 Transfer Functions and Time Responses to an Idealized Doublet in Fifth-order Lateral Dynamics

From Equations 3.38 and 3.45, the analytical solution for the state vector in the 'Laplace s-realm' is obtained. The former equation yields for the 'system matrix'

$$sI - \Phi = \begin{pmatrix} s & 0 & 0 & 0 & 0 \\ -V/(aT_\psi) & s + 1/T_\psi & 0 & 0 & 0 \\ -1/(2T_\beta) & 1 & s + 1/T_\beta & 0 & 0 \\ 0 & -1 & 0 & s & 0 \\ 0 & 0 & -V & -V & s \end{pmatrix}. \tag{B.5}$$

By multiplication of Equation 3.45 from the left by $(sI - \Phi)^{-1}$, there follows

$$\underline{x}_{La}(s) = (sI - \Phi)^{-1} \cdot \underline{b} \cdot u(s) + (sI - \Phi)^{-1} \cdot \underline{x}_{La}(0). \tag{B.6}$$

The first term defines the five transfer functions of a control input u(s) while the second term gives the response to initial values in the state variables. All these expressions have a common denominator, the characteristic polynomial $D(s)$ of the determinant det $(sI - \Phi)$

$$D = s^3 (s + 1/T_\psi)(s + 1/T_\beta)\,. \tag{B.7}$$

The numerator polynomials of the transfer functions are obtained by the determinants in which the column corresponding to the state variable of interest has been replaced by the coefficient vector $\underline{b}$ for control input. This yields the numerator terms for the heading angle ψ and the lateral position y

$$\begin{aligned} N_\psi &= [V/(a \cdot T_\psi)] \cdot s \cdot (s + 1/T_\beta) \\ N_y &= Va/(2T_\beta) \cdot [s^2 + s/T_\psi + 2V/(a \cdot T_\psi)]. \end{aligned} \tag{B.8}$$

With the doublet input of Equation 3.44, $u_{\text{idd}}(s) = A \cdot s$, the resulting state variables yaw angle $\psi(s)$ and the lateral acceleration in the y direction $s^2 \cdot y(s)$ are in the Laplace-domain

$$\begin{aligned} \psi(s) &= [N_\psi \;/ D] \cdot A \cdot s \\ &= A \cdot s\; [V/(a\; T_\psi)] \cdot s\; (s\; + 1/T_\beta)/[\; s^3 \cdot (s\; + 1/T_\beta)(s + 1/T_\psi)] \\ &= A\; V/(a\; T_\psi)/[s\; (s\; + 1/T_\psi)] \\ &= A\; V/(a\; T_\psi) \cdot [1/s - 1/(s\; + 1/T_\psi)]. \end{aligned} \tag{B.9}$$

$$\begin{aligned} a_y(s) &= s^2 \cdot y(s) = N_y \cdot A \cdot s^3 / D \\ &= A\; V/T_\beta \cdot s^3 \cdot [s^2 + s/T_\psi + 2V/(a \cdot T_\psi)]/D \\ &= Va/(2T_\beta) \cdot [1(s) + B/(s + 1/T_\psi) - (B\; +\; 1/T_\beta)/(s + 1/T_\beta)], \\ &\qquad \text{with} \quad B \;=\; 2V/[a \cdot (T_\psi / T_\beta - 1)]. \end{aligned} \tag{B.10}$$

The expression $1/s$ in Equation B.9 corresponds in the time domain to a unit step function, and the second term in Equation B.9: $c/(s + 1/T_i)$ to: $c \cdot \exp[-(t/T_i)]$. This yields with Equation 3.36 after back-transformation into the time domain

$$\psi(t)_{\text{doublet}} \;=\; A \cdot k_{ltf} /(a \cdot i_{zB}^2) \cdot [1 - \exp(-\, t / T_\psi)]\,. \tag{B.11}$$

$1(s)$ in Equation B.10 corresponds to a *'Dirac impulse' δ(0)* at time 0 with an integral value of 1 (a step function in the integrated variable, the lateral velocity $v_y = \int a_y dt$ experiences a jump from 0 to 1 at t = 0). Introducing this and the relations given in Equation 3.37 into Equation B.10 yields for the time functions

$$a_y(t) = A \cdot k_{ltf} \cdot \left\{ 0.5 \cdot \delta(0) + \frac{V}{a(1 - i_{zB}^2)} \cdot \left[e^{-t/T_\beta} - e^{-t/T_\psi} \right] - \frac{0.5 \cdot k_{ltf}}{V} e^{-t/T_\beta} \right\} \tag{B.12 (a)}$$

$$= \frac{A}{2} \cdot k_{ltf} \cdot \delta(0) \;+ e^{-t/T_\beta} \cdot \left\{ \frac{VA\, k_{ltf}}{a(1 - i_{zB}^2)} \cdot \left[1 - e^{-t/T_{\beta\text{mod}}} \right] - \frac{A\, k_{ltf}^2}{2V} \right\}, \tag{b}$$

where $T_{\beta\text{mod}} = T_\beta \cdot i_{zB}^2 /(1 - \; i_{zB}^2)$.

The value $T_{\beta\text{mod}} / T_\beta = i_{zB}^2 /(1 - i_{zB}^2)$ is 2.77 for VaMoRs and 5.67 for VaMP. Figure B.1 shows the principal time histories of the exponential functions in scaled form for VaMoRs. The yaw angle goes from zero to $[A \cdot k_{ltf} / (a \cdot i_{zB}^2)]$ with time constant T_ψ. According to Equation 3.37, T_ψ increases linearly with speed.

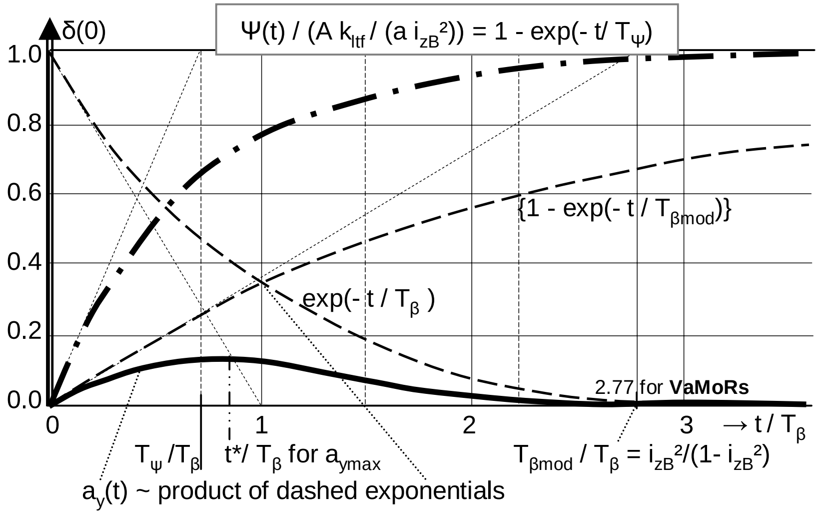

Figure B.1. Scaled dynamic response in yaw angle (*dash-dotted*) and lateral acceleration (*solid curve*) to doublet input in steering rate (see Equations B.11/B.12); the time axis is scaled by T_β

Appendix C
Recursive Least-squares Line Fit

Through a set of measurement points (y_{m1} … y_{mN}), equidistantly spaced on the abscissa (x_1 = 0.5, 1.5 …. N−0.5), a straight line shall be fit recursively with interpolated measurement points (y_1 … y_N), if the standard deviation remains below a threshold value σ_{maxth} and the new measurement point to be added is within a 3σ band around the existing fit. The resulting set of smoothed measurement data will be called a segment or a 1-D blob. The result shall be represented by the average value y_c in the segment, with the origin at the segment center x_c, and the (linear) slope ‘a’ around this center (see Figure C.1). A deviation from the usual terminology occurs because image evaluation with symmetric masks has its origin right between pixel boundaries; the reference pixel for mask evaluation has been selected at position (0.5, 0.5) of the mask (see Figure 5.19).

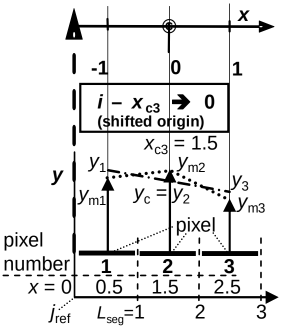

Figure C.1. Nomenclature used with integer basic scale for pixels; origin of centered scale at N/2

This definition leads to the fact that x_c is either an integer or lies exactly at the center between two integers (i − 0.5). Due to the integer values for the pixels and because a new segment is always started with the *reference coordinate* j_{ref} for x_0 = 0, the center of N values is located at

$$x_{c,abs} = j_{ref} + N/2 = j_{ref} + x_c\,. \qquad \text{(C.1)}$$

C.1 Basic Approach

Since two measurement points can always be connected by a straight line, interpolation starts at the third point into a new segment. The general form of the interpolating straight line with x_c as the center of all x_i is

$$\begin{aligned} y_i &= y_c + a \cdot \Delta x_i \\ \text{with} \quad \Delta x_i &= x_i - x_c. \end{aligned} \qquad \text{(C.2)}$$

y_c is always taken at the center of the data set, and ‘a’ is the slope of the line. This yields for the residues $e_i = y_i - y_{mi}$ (see Figure C.1) the set of equations:

$$\begin{aligned} e_1 &= y_c + (x_1 - x_c)\cdot a - y_{m1}, \\ e_2 &= y_c + (x_2 - x_c)\cdot a - y_{m2}, \\ e_3 &= y_c + (x_3 - x_c)\cdot a - y_{m3}. \end{aligned} \qquad \text{(C.3)}$$

For easy generalization, this is written in matrix form with the two unknown variables: average value y_c of the interpolating straight line and slope a. The measurement vector y_m has length N, with the original running index i linearly increasing from 1 to N; measurement values of the pixels then are located at x-position [(pixel index i) − 0.5]; the initial value for N is 3 (Figure C.1). The running index for the shifted scale with $x_c = 0$ then goes from − N/2 to + N/2. With the model of Equation C.2, the errors are

$$[e]=\begin{bmatrix}1 & x_1-x_c\\ \cdot & \cdot\\ 1 & x_i-x_c\\ \cdot & \cdot\\ 1 & x_N-x_c\end{bmatrix}\cdot\begin{bmatrix}y_c\\ a\end{bmatrix}-[y_m]_N=A\cdot p-[y_m]_N\,. \tag{C.3a}$$

The sum J of the squared errors can now be written

$$J=\sum_{i=1}^{n}e_i^2=e^Te=(A\cdot p-y_m)^T(A\cdot p-y_m)\,. \tag{C.4}$$

The same procedure as in Section 5.3.2.1, setting the derivative dJ/dp = 0, leads to the optimal parameters p_{extr} for minimal J:

$$\begin{pmatrix}y_c\\ a\end{pmatrix}_{LS}=p_{extr}=(A^TA)^{-1}A^Ty_m\,. \tag{C.5}$$

With $x_i = i - 0.5$ from 0.5 to $N - 0.5$, and with Equation C.3a the product A^TA can be written

$$A^TA=\begin{bmatrix}1 & .. & 1 & .. & 1\\ 0.5-x_c & .. & i-0.5-x_c & .. & N-0.5-x_c\end{bmatrix}\cdot\begin{bmatrix}1 & 0.5-x_c\\ \cdot & \cdot\\ 1 & i-0.5-x_c\\ \cdot & \cdot\\ 1 & N-0.5-x_c\end{bmatrix} \tag{C.6}$$

$$=\begin{bmatrix}N & a_{12}\\ a_{21} & a_{22}\end{bmatrix}.$$

By always choosing the center of gravity of the abscissa values x_c as reference and by shifting the indices correspondingly (see lower part of Figures C.1 and C.2), there follows

$$a_{21}=a_{12}=\sum_{i=1}^{N}(i-0.5-x_c)=0\,. \tag{C.7}$$

For each positive index in the shifted coordinates (lower part of figures), there is a corresponding negative one, yielding Equation C.7. This means that A^TA is zero off the main diagonal. For a_{22} in Equation C.6 one obtains

$$a_{22}=\sum_{i=1}^{N}(i-0.5-x_c)^2=\sum_{i=1}^{N}(i^2-2\cdot i\cdot x_c+x_c^2+0.25+x_c-i)\,. \tag{C.8}$$

Introducing the well-known relations

$$\sum_{i=1}^{N}i=N(N+1)/2\,, \tag{C.9}$$

$$\sum_{i=1}^{N} i^2 = N(N+1)(2N+1)/6\,, \tag{C.10}$$

the following result for a_{22} is obtained with $x_c = N/2$ after several steps

$$a_{22} = N(N^2-1)/12. \tag{C.11}$$

With Equations C.7 and C.11 the inverse of A^TA (Equation C.6) becomes

$$(A^T A)^{-1} = \begin{pmatrix} 1/N & 0 \\ 0 & 1/a_{22} \end{pmatrix}. \tag{C.12}$$

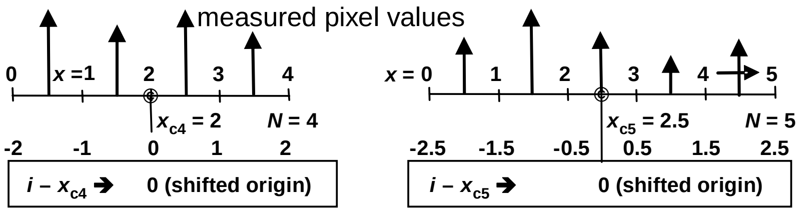

Figure C.2. Centered coordinates for even and odd numbers of equidistant grid points; this choice reduces the numerical workload

To obtain the optimal parameters for a least squares fit according to Equation C.6, the factor $A^T y_m$ has yet to be determined:

$$A^T y_m = \begin{bmatrix} 1 & .. & 1 & .. & 1 \\ 1-0.5-x_c & .. & i-0.5-x_c & .. & N-0.5-x_c \end{bmatrix} \cdot \begin{bmatrix} y_{m1} \\ . \\ y_{mi} \\ . \\ y_{mn} \end{bmatrix}_N \tag{C.13}$$

$$= \begin{bmatrix} Sym \\ Siym - 0.5 \cdot Sym - x_c \cdot Sym \end{bmatrix},$$

$$\text{with} \quad Sym = \sum_{i=1}^{N} y_{mi} \quad \text{and} \quad Siym = \sum_{i=1}^{N} (i \cdot y_{mi}). \tag{a}$$

Inserting this, the relation $x_c = N/2$, and Equation C.11 into C.5, the following optimal parameters y_c and a are finally obtained:

$$\begin{pmatrix} y_c \\ a \end{pmatrix}_{LS} = \begin{pmatrix} 1/N & 0 \\ 0 & 1/a_{22} \end{pmatrix} \cdot \begin{pmatrix} Sym \\ Siym - \dfrac{N+1}{2} Sym \end{pmatrix} \tag{C.14}$$

or

$$\begin{pmatrix} y_c \\ a \end{pmatrix}_{LS} = \begin{bmatrix} Sym/N \\ \left(Siym - \dfrac{N+1}{2} Sym \right) / a_{22} \end{bmatrix} = \begin{bmatrix} Sym/N \\ \dfrac{6}{N-1} \left(\dfrac{2}{N+1} \cdot \dfrac{Siym}{N} - \dfrac{Sym}{N} \right) \end{bmatrix}. \tag{C.14 (a)}$$

y_c is nothing but the average value of all measurements y_{mi}; to obtain the optimal slope a, the product $i \cdot y_{mi}$ has to be summed, too (Equation C.13a). It is seen that for this least-squares fit with a cg-centered coordinate system ($y(0) = y_c$), where this origin moves in steps by 0.5 with N increasing by 1, just four numbers have to be stored: The number of data points N, the averaged sum of all measured values $y_c = Sym/N$, the averaged sum of all products $(i \cdot y_{mi})$: $Siym/N$, and, of course, the reference for i =1 where the data set started; this yields the optimal parameters: 'y_c = *average value at the segment center*' and 'a = *slope*' for the best interpolating straight line by just a few mathematical operations independent of segment length n.

C.2 Extension of Segment by One Data Point

Let the existing segment have length N; the averaged sums Sym/N and $Siym/N$ (Equation C.13) have been stored. If one new measurement value arrives, its expected magnitude according to the existing model can be computed. The number of measurements increases by 1, and the new segment center x_{ce} shifts to

$$N_e = N+1; \quad x_{ce} = N_e/2 = x_c + 0.5. \tag{C.15}$$

The predicted measurement value according to the linear model is

$$y_{mpr} = y_c + a \cdot (N+1-x_c) = y_{cpr} + a(N_e - x_{ce}) . \tag{C.16}$$

Since the new origin x_{ce} is shifted to the right by 0.5, the expected average value y_{cpr} will be shifted by $a/2$, yielding the rightmost part of Equation C.16. The new measurement value y_{mNe} will be accepted as extension of the segment only if

$$\begin{aligned} &| y_{mNe} - y_{mpr} | \le 3 \cdot \sigma, \\ \text{or} \quad &(y_{mNe} - y_{mpr})^2 \le 9 \cdot \sigma^2, \end{aligned} \tag{C.17}$$

with σ^2 as variance of all previous measurements; otherwise, the segment is concluded with the original value for N.

If the segment is extended, the new parameters for best fit are, according to Equation C.14a

$$\begin{aligned} y_{ce} &= \frac{Sym_e}{N_e} = \left[\left(\frac{Sym}{N} \right) \cdot \frac{N}{N_e} + \frac{\mathrm{y}_{\mathrm{mNe}}}{N_e} \right]; \\ a_e &= \frac{6}{N_e - 1} \cdot \left(\frac{Siym_e / N_e}{x_{ce}} - y_{ce} \right) \\ &= \frac{6}{N_e - 1} \left\{ \frac{1}{x_{ce}} \cdot \left[\left(\frac{Siym}{N} \right) \cdot \frac{N}{N_e} + \mathrm{y}_{\mathrm{mNe}} \right] - y_{ce} \right\}. \end{aligned} \tag{C.18}$$

The terms in rounded brackets are the stored (original) values, while the terms in squared brackets are the new values for $N_e = N+1$ to be stored. The definition of the variance is

$$Var(e)_N := \frac{1}{N-1} \sum_{i=1}^{N} e_i^2 = J/N \quad \text{(with Equation C.4).} \tag{C.19}$$

Inserting the result C.14a for p in J, and exploiting the relations C.1 and C.6 to C.13, one obtains, with $y_m^T y_m = \sum_{i=1}^{N} y_{mi}^2 = Sy2m$ as shorthand notation,

$$Var(e)_N = \frac{Sy2m}{N-1} - f\left(Siym,\ N,\ a,\ x_c,\ y_c\right). \qquad \text{(C.19a)}$$

To be able to compute the variance recursively, the sum of the squared measurement values *Sy2m* (divided by $N-1$) also has to be stored as an entry into Equation C.19a. The recursive update from N to $N+1$ is given below (on the right side)

$$\frac{Sy2m}{N} = \frac{1}{N}\sum_{i=1}^{N} y_{mi}^2 \quad \text{or} \quad \frac{Sy2m_e}{N_e} = \left[\frac{N}{N_e}\cdot\left(\frac{Sy2m}{N}\right) + \frac{y_{mNe}^2}{N_e}\right]. \qquad \text{(C.20)}$$

This shows that the new stored value (in square brackets) results from the old one (in rounded brackets) weighted by the factor N/N_e and the squared new measurement value weighted by $1/N_e$. Since the rather complex expressions for the variance are not used in the real-time algorithm, they are not discussed in detail here (see next section).

C.3 Stripe Segmentation with Linear Homogeneity Model

Instead of comparing the magnitude of the prediction error with the 3σ-value of the existing fit, as a criterion for acceptance of the next measurement point, the less computer-intensive criterion in the lower part of Equation C.17 is used:

$$(y_{mpr} - y_{mNe})^2 \le 9\cdot\sigma_N^2 = 9\cdot(Var(e)\,|_N)\,,$$

or even (C.21)

$$(y_{mpr} - y_{mNe})^2 \le \text{variance limit (VarLim)}\,.$$

VarLim is a fixed threshold parameter of the method; for typical intensity values of video signals (8 to 10 bit, 256 to 1k levels) and the sensitivity of the human eye (~ 60 levels), threshold values 4 ≤ VarLim ≤ 225 seem reasonable. With Equation C.21, acceptance can be decided without computing the new fit and the new variance. The influence of the new measurement point on the parameters for optimal fit is neglected.

The second method is to compute all new parameters including the new variance and to compare the residue

$$e_{Ne} = y_{cNe} + a_{Ne}\cdot(N_e - x_{ce}) - y_{mNe} \qquad \text{(C.22)}$$

squared of the new measurement point N_e with the newly determined variance

$$e_{Ne}^2 \le 9\cdot\sigma_{Ne}^2 = 9\cdot(Var(e)\,|_{Ne})\,. \qquad \text{(C.23)}$$

When the new value is accepted, store all updated values:

$$N = N_e;\quad \frac{Sym}{N} = \frac{Sym_e}{N_e};\quad \frac{Siym}{N} = \frac{Siym_e}{N_e};\quad \frac{Sy2m}{N} = \frac{Sy2m_e}{N_e};$$
$$y_c = y_{ce};\quad x_c = x_c + 0.5;\quad a = a_e;\quad Var(e)\,|_N = Var(e)\,|_{Ne}\,. \qquad \text{(C.24)}$$

Now the next value can be tested with the same procedure.

C.4 Dropping Initial Data Point

This segment reduction at the start may sometimes have beneficial effects on the quality of the linear fit. After several data points have been interpolated by a straight line, the variance of the whole set may be reduced by dropping the first point or a few initial points from the segment. An indication for this situation is given when the first residue on the left side is larger than the standard deviation of the segment. To check this, the interpolated value at location i = 1 has to be computed with the parameter set (y_{cN} and a_N) after N data points

$$e_{1N} = y_{cN} + a_N \cdot (1 - x_{cN}) - y_{m1} . \tag{C.25}$$

For computational efficiency again the variance is taken as a base for decision: If

$$(e_1)_N^2 \geq Var(e)\,|_N , \tag{C.26}$$

dropping the first data point will decrease the variance of the remaining data set. The even simpler check with a fixed threshold

$$(e_1)_N^2 \geq VarLim \tag{C.26a}$$

has proven well suited for efficient real-time computation.

With the stored values of Equation C.24 and always working with locally centered representations, the reduction at the left is directly analogous to the extension at the right-hand side. The problematic point is the sum *Siym* of the products (local index times measurement value) (Equation C.13a and C.18). The new starting point of the segment will become (x_{ref} + 1), but the length N_{red} of the segment will be reduced by 1, while the position of its center is reduced by −0.5 for symmetry; i in *Siym* has to be decremented

$$x_{ref} := x_{ref} + 1; \quad N_{red} = N - 1; \quad x_{cred} = x_c - 0.5;$$

$$Siym_{red} = N \sum_{j=2}^{N} (j-1) \cdot y_{mj} = \sum_{i_{red}=1}^{N_{red}} i_{red} \cdot y_{mi_{red}} = \sum_{j=2}^{N} j \cdot y_{mj} - \sum_{j=2}^{N} y_{mj} . \tag{C.27}$$

By noting that

$$Siym_N = y_{m1} + \sum_{i=2}^{N} i \cdot y_{mi}; \quad Sym_N = y_{m1} + \sum_{i=2}^{N} y_{mi} , \tag{C.28}$$

adding 0 = ($y_{m1} - y_{m1}$) to the lower Equation C.27 immediately yields

$$\begin{aligned} Siym_{red} &= y_{m1} + \sum_{j=2}^{N} j \cdot y_{mj} - (y_{m1} + \sum_{j=2}^{N} y_{mj}) = Siym_N - Sym_N ; \\ Sym_{red} &= Sym_N - y_{m1}. \end{aligned} \tag{C.29}$$

This leads to the *recursive procedure* that is to be executed as long as the initial residue squared is larger than the threshold 'variance limit':

$$\begin{aligned} &N_{red} = N - 1; \quad x_{\text{ref}} := x_{\text{ref}} + 1; \quad x_{cred} = x_c - 0.5; \\ &Siym_{red} = Siym_N - Sym_N ; \quad Sy2m_{red} = Sy2m_N - y_{m1}^2; \\ &Sym_{red} = SymN - y_{m1}; \quad y_{cred} = Sym_{red}/N_{red} ; \\ &a_{red} = \frac{6}{N_{red} - 1}\left(\frac{2}{N_{red} + 1} \cdot \frac{Siym_{red}}{N_{red}} - y_{cred} \right). \end{aligned} \tag{C.30}$$

The maximum number k of points to be dropped will not be large, in general, since otherwise the segment would have been ended during normal extension.

After reducing the segment length at the side of low indices i, increasing the segment at the other end should be tried again. Figure 5.32 has been interpolated without dropping terms at the left side of the segment, from which the line fit was started. The first longer segment from ~ row = 90 to 115 (upper left center in the figure, designated as 'blob 1') could profit from dropping the leftmost data point since a steeper negative value for a_{red} can fit several following data points better. (dotted line, Figure C.3 shows a blown up view of blob 1 of Figure 5.32. The solid line is the least-squares line fit resulting without a check of the residue of the 'first' data point after each update; interpolation is stopped at the solid black dots (lower right) because the variance exceeds the threshold set.

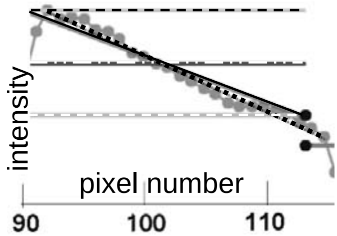

Figure C.3. Large threshold values for starting a line fit (upper left corner) may lead to suboptimal results (see text)

Dropping the 'first' data point (top left) allows a much better fit to the remaining points; it even allows an extension of the segment to larger values L_{seg} (two more data points) The dotted line in Figure C.3 shows an improved fit with reduced total variance.

Figure 5.35 shows several cases of this type of blob data fit, with the method described here, for a number of columns of a video field. In the top left subfigure, the white lines mark the cross sections selected. Some correspondences between object regions in the scene and blob parameters are given. The task of hypothesis generation in vision is to come up with most reasonable object hypotheses given a collection of features (blobs, edges and corners); homogeneous areas with center of gravity, shape as well as shading parameters are a big step forward compared to just edge features with adjacent average gray values available in real-time evaluation about fifteen years ago.

Figure C.4 (next page) shows the flowchart of the segmentation algorithm including size adaptation at both ends for an optimal fit of shaded stripe segments.

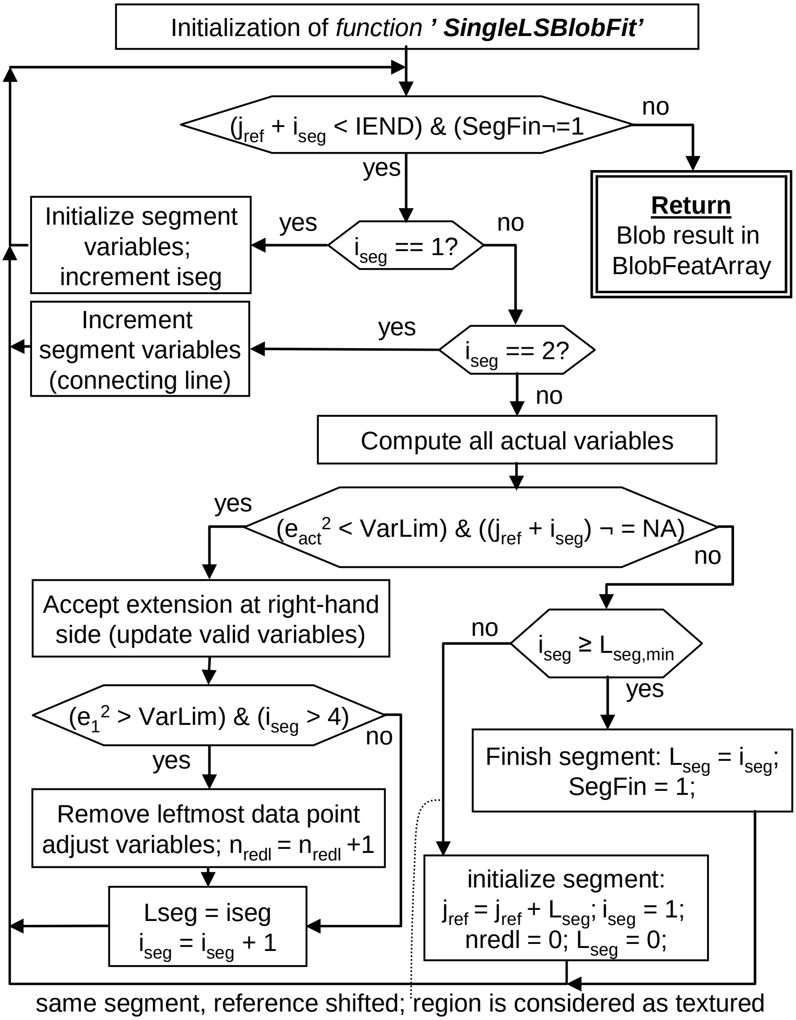

Figure C.4. Flowchart of segmentation method for linearly shaded regions including boundary adaptation at both ends (Matlab®-terminology)

References

Albus J.S., Meystel A.M. (2001): Engineering of Mind. – An Introduction to the Science of Intelligent Systems. Wiley Series on Intelligent Systems

Alexander R. (1984): The gaits of bipedal and quadrupedal animals. Journal of Robotics Research 3(2)

Aloimonos J., Weiss I., Bandyopadhyay A. (1987): Active vision. Proceedings 1st Int. Conf. on Computer Vision: 35–54

Altmannspacher H., Ruhnau E. (eds) (1997): Time, Temporality, Now. Springer–Verlag, Berlin

Arbib M.A., Hanson A.R. (eds) (1987): Vision, Brain, and Cooperative Computing. MIT Press, Cambridge, MA

Arkin R. (1998): Behavior-Based Robotics. MIT Press, Cambridge, MA

Baghdassarian C., Lange H., Sahli, Laurgeau C. (1994): Recognition of arrows in the environment of road markings. Proc. Int. Symp. on Intell. Vehicles'94, Paris: 219–224

Ballard D.H. (1991): Animate vision. Artificial Intelligence 48: 57–86

Ballard D.H., Brown C.M. (1982): Computer Vision. Prentice–Hall, Englewood Cliff, NJ

Bar Shalom Y., Fortmann T.E. (1988): Tracking and Data Association. Mathematics in Science and Engineering, Academic Press

Bar Shalom Y., Li X.R. (1998): Estimation and Tracking: Principles, Techniques, and Software. Danvers, MA; YBS

Behringer R. (1996): Visuelle Erkennung und Interpretation des Fahrspurverlaufes durch Rechnersehen für ein autonomes Straßenfahrzeug. Diss. UniBw Munich, LRT; also: Fortschrittberichte VDI, Reihe 12, Nr. 310

Bergen J.R. (1990) Dynamic Analysis of Multiple Motion. Proc. Israeli Conference on Artificial Intelligence and Computer Vision. Tel Aviv

Bertozzi M., Broggi A., Fascioli A. (2000): Vision-based intelligent vehicles: State of the art and perspectives. Robotics and Autonomous Systems 32: 1–16

Bertozzi M., Broggi A., Fascioli A., Tibaldi A., Chapuis R., Chausse, F. (2004): Pedestrian Localization and tracking System with Kalman Filtering. Proceedings IEEE International Symposium on Intelligent Vehicles, Parma: 584–590

Besl P.J., Jain R.C. (1995): Three dimensional object recognition. ACM Comput. Surveys 17(1): 75–145

Bierman G.J. (1975): Measurement Updating Using the U-D Factorization. Proc. IEEE Control and Decision Conf., Houston. TX: 337–346

Bierman G.J. (1977): Factorization Methods for Discrete Sequential Estimation. Academic Press, New York

Blake A., Zisserman A. (1987): Visual Reconstruction. MIT Press, Cambridge, MA

Blake A., Yuille A. (1992): Active Vision. MIT Press, Cambridge, MA

Blinn J.A. (1977): A Homogeneous Formulation for Lines in 3 Space. Proc. of SIGGRAPH 77. In Computer Graphics 11(3)

Bohrer S., Zielke T., Freiburg V. (1995): An integrated obstacle detection framework for intelligent cruise control on motorways. Proceedings International Symposium on Intelligent Vehicles, Detroit

Braess H.H., Reichart G. (1995a): Prometheus: Vision des ‘intelligenten Automobils’ auf ‘intelligenter Straße’? Versuch einer kritischen Würdigung – Teil 1. ATZ Automobiltechnische Zeitschrift 97, Bd 4: 200–205

Braess H.H., Reichart G. (1995b): Prometheus: Vision des ‘intelligenten Automobils’ auf ‘intelligenter Straße’? Versuch einer kritischen Würdigung – Teil 2. ATZ Automobiltechnische Zeitschrift 97, Bd. 6: 330–343

Brammer K., Siffling G. (1975): Kalman-Bucy-Filter.Deterministische Beobachtung und stochastische Filterung. Oldenbourg Verlag, Muenchen, Wien

Broggi A., Cerri P., Antonello P.C. (2004): Multi-resolution Vehicle Detection using Artificial Vision. Proceedings International Symposium on Intelligent Vehicles, Parma: 310–314

Brooks R.A. (1986): A robust layered control system for a mobile robot. IEEE-J. of Robotics and Automation, 2: 14–23

Brauckmann M.E., Goerick C., Gro J.; Zielke T. (1994): Towards All Around Automatic Visual Obstacle Sensing for Cars. Proceedings International Symposium on Intelligent Vehicles, Paris: 79–84

Bruderlin A., Calvert T.W. (1989): Goal-directed, dynamic animation of human walking. Computer Graphics 23(3), ACM SIGGRAPH, Boston

Brüdigam C. (1994): Intelligente Fahrmanoever sehender autonomer Fahrzeuge in autobahnaehnlicher Umgebung. Diss. UniBw Munich, LRT

Burt P.J., Hong T.H., Rosenfeld H. (1981): Segmentation and estimation of image region properties through cooperative hierarchical computation. IEEE Trans. Systems, Man, and Cybernetics, **11**(12): 802–825

Canny J.F. (1983): A computational approach to edge detection. IEEE-Trans. Pattern Analysis and Machine Intelligence (PAMI) 8 (6): 679–698

Carlson S., Eklundh J.O. (1990): Object detection using model based prediction and motion parallax. In: Proc. European Conference on Computer Vision (ECCV’90), France: 297–306

Davis L., Kushner T.R., Le Moigne J.J., Waxman A.M. (1986): Road Boundary Detection for Autonomous Vehicle Navigation. Optical Engineering, 25(3): 409–414

Debusschere I., Bronckaers E., Claeys C., Kreider G., Van der Spiegel J., Sandini G., Dario P., Fantini F., Bellutti P., Soncini G. (1990): A Retinal CCD Sensor for Fast 2D Shape, Recognition and Tracking. Sensors and Actuators, A21: 456–460

Deriche R., Giraudon G. (1990): Accurate Corner Detection: An Analytical Study. Proc. International Conference on Computer Vision (ICCV), 1990: 66–70

Dickmanns D. (1995): Knowledge based real-time vision. Proc. 2^{nd} IFAC Conf. on Intelligent Autonomous Vehicles, Helsinki

Dickmanns D. (1997): Rahmensystem für visuelle Wahrnehmung veränderlicher Szenen durch Computer. Diss., UniBw Munich, INF. Also: Shaker Verlag, Aachen, 1998

Dickmanns E.D. (1985): 2-D-Object Recognition and Representation using Normalized Curvature Functions. In M.H. Hamza (ed): Proc. IASTED International Symposium on Robotics and Automation, Acta Press: 9–13

Dickmanns E.D., Zapp A. (1986): A Curvature-based Scheme for Improving Road Vehicle Guidance by Computer Vision. In: 'Mobile Robots', SPIE Proc. 727, Cambridge, MA: 161–168

Dickmanns E.D. (1987): 4-D Dynamic Scene Analysis with Integral Spatio-Temporal Models. In: Bolles R, Roth B(eds.): Robotics Research, 4th International Symposium, MIT Press, Cambridge MA

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

Dickmanns E.D., Graefe V. (1988): (a) Dynamic monocular machine vision. Journal of Machine Vision and Application, Springer International 1:223-240. (b) Applications of dynamic monocular machine vision. *(ibid)*: 241–261

Dickmanns E.D. (1988): Object Recognition and Real-Time Relative State Estimation Under Egomotion. In: Jain AK(ed) (1988): Real-Time Object Measurement and Classification. Springer-Verlag, Berlin: 41–56

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

Dickmanns E.D., Christians T. (1989): Relative 3-D state estimation for autonomous visual guidance of road vehicles. In: Kanade, T. *et al*. (eds.): 'Intelligent Autonomous Systems 2', Amsterdam, Dec. 1989, Vol.2 pp. 683-693; also appeared in: Robotics and Autonomous Systems 7 (1991): 113 – 123

Dickmanns E.D., Mysliwetz B., Christians T. (1990): Spatio-Temporal Guidance of Autonomous Vehicles by Computer Vision. IEEE-Trans. on Systems, Man and Cybernetics, 20(6), Special Issue on Unmanned Vehicles and Intelligent Robotic Systems: 1273–1284

Dickmanns E.D., Mysliwetz B. (1992): Recursive 3-D Road and Relative Ego-State Recognition. IEEE-Trans. Pattern Analysis and Machine Intelligence (PAMI) 14(2), Special Issue on 'Interpretation of 3-D Scenes': 199–213

Dickmanns E.D., Behringer R., Dickmanns D., Hildebrandt T., Maurer M., Thomanek F., Schiehlen J. (1994): The Seeing Passenger Car 'VaMoRs-P'. In Masaki I (ed): Proceedings International Symposium on Intelligent Vehicles'94, Paris: 68–73

Dickmanns E.D. (1995): Road vehicle eyes for high precision navigation. In Linkwitz *et al*. (eds) (1995) High Precision Navigation. Dummler Verlag, Bonn: 329–336

Dickmanns E.D., Müller N. (1995): Scene Recognition and Navigation Capabilities for Lane Changes and Turns in Vision-Based Vehicle Guidance. Control Engineering Practice, 2nd IFAC Conf. on Intelligent Autonomous Vehicles'95, Helsinki; also published in Control Engineering Practice (1996), 4(5): 589–599

Dickmanns E.D., Wuensche H.J. (1999): Dynamic Vision for Perception and Control of Motion. In: Jaehne B., Haußenecker H., Geißler P. (eds): Handbook of Computer Vision and Applications, Vol. 3, Academic Press: 569–620

Dickmanns E.D. (2002a): The development of machine vision for road vehicles in the last decade. Proceedings International Symposium on Intelligent Vehicles'02, Versailles

Dickmanns E.D. (2002b): Vision for ground vehicles: History and prospects. International Journal of Vehicle Autonomous Systems, 1(1): 1–44

Dickmanns E.D. (2003): Expectation-based, Multi-focal, Saccadic Vision - (Understanding dynamic scenes observed from a moving platform). In: Olver P.J., Tannenbaum A. (eds) (2003) Mathematical Methods in Computer Vision, Springer-Verlag: 19–35

Duda R., Hart P. (1973): Pattern classification and scene analysis. Wiley, New York

Ehrenfels C.V. (1890): Über Gestaltqualitäten. Vierteljahresschrift für wissenschaftliche Philosophie, Bd 14

Enkelmann W. (1990): Obstacle Detection by Evaluation of Optical Flow Fields from Image Sequences. In: Proc. ECCV 90, France: 134–138

Estable S., Schick J., Stein F., Janssen R., Ott R., Ritter W., Zheng Y.J. (1994): A Real-Time Traffic Sign Recognition System. Proceedings International Symposium on Intelligent Vehicles’94, Paris: 213–218

Fagerer C., Dickmanns E.D., Dickmanns D. (1994): Visual Grasping with Long Delay Time of a Free Floating Object in Orbit. J. Autonomous Robots, 1(1)

Fifth Workshop on Massively Parallel Processing (2005), Denver, CO

Fikes R., Nilsson N. (1971): STRIPS: A New Approach to the Application of Theorem Proving to Problem Solving. Artificial Intelligence, 2: 189–208

Fleischer K., Nagel H.H., Rath T.M. (2002): 3D-Model-based Vision for Innercity Driving Scenes. Proceedings International Symposium on Intelligent Vehicles’02, Versailles

Florack L.M.J., ter Haar Romeny B.M., Koenderink J.J., Viergever M.A. (1992): Scale and the differential structure of images. Image and Vision Computing, 10(6): 376–388

Foley J.D., van Dam A., Feiner S., Hughes J.F. (1990): Computer Graphics – Principles and Practice. Addison-Wesley

Franke U. (1992): Real time 3D-road modeling for autonomous vehicle guidance. In: Johanson, Olson (1992) Selected Papers of 7th Scandinavian Conference on Image Analysis. World Science Publishing Company: 277–284

Franke U., Rabe C., Badino H., Gehrig S.K. (2005): 6D-Vision: Fusion of Stereo and Motion for Robust Environment Perception. Proceedings Deutsche Arbeitsgemeinschaft für Mustererkennung (DAGM), Symposium 2005: 216–223

Freeman H. (1974): Computer processing of line-drawing images. Computing Surveys, 6(1): 57–97

Fritz H. (1996): Model-Based Neural Distance Control for Autonomous Road Vehicles. Proceedings International Symposium on Intelligent Vehicles’96, Tokyo: 29–34

Gauss C.F. (1809): Theoria Motos Corporum Coelestium. Goettingen. Republished in 1857, and by Dover in 1963 by Little, Brown and Co.

Gelb A. (ed) (1974): Applied Optimal Estimation. MIT Press

Giampiero M. (2007): Handbook of Road Vehicle Dynamics. CRC Press (in press)

Graefe V. (1984): Two Multi-Processor Systems for Low Level Real-Time Vision. In: Brady J.M., Gerhard L.A., Davidson H.F. (eds) (1984): Robotics and Artificial Intelligence, Springer–Verlag: 301–307

Graefe V. (1989): Dynamic vision systems for autonomous mobile robots. Proceedings, IEEE/RSJ International Workshop on Intelligent Robots and Systems, Tsukuba: 12–23

Graefe V., Efenberger W. (1996): A Novel Approach for the Detection of Vehicles on Freeways by Real-time Vision. Proceedings International Symposium on Intelligent Vehicles, Tokyo: 363–368

Gregor R., Lützeler M., Pellkofer M., Siedersberger K.H., Dickmanns E.D. (2000): EMS-Vision: A Perceptual System for Autonomous Vehicles. Proceedings International Symposium on Intelligent Vehicles, Dearborn, MI: 52–57

Gregor R., Dickmanns, E.D. (2000): EMS-Vision: Mission Performance on Road Networks. Proceedings International Symposium on Intelligent Vehicles, Dearborn, MI: 140–145

Gregor R., Luetzeler M., Dickmanns E.D. (2001): EMS-Vision: Combining on- and off-road driving. Proc. SPIE-Aero-Sense, Orlando, FL

Gregor R., Lützeler M., Pellkofer M., Siedersberger K.H., Dickmanns E.D. (2001): A Vision System for Autonomous Ground Vehicles with a Wide Range of Maneuvering Capabilities. Proc. ICVS, Vancouver

Gregor R., Lützeler M., Pellkofer M., Siedersberger K.H. and Dickmanns E.D. (2002): EMS-Vision: A Perceptual System for Autonomous Vehicles. IEEE Transactions on Intelligent Transportation Systems, 3(1): 48–59

Gregor R. (2002): Faehigkeiten zur Missionsdurchfuehrung und Landmarkennavigation. Diss. UniBw Munich, LRT

Handbook of Physiology, American Physiological Society:
Brooks VB (ed) (1987): Motor Control, Vol. II, Parts 1 and 2
Darian-Smith I (ed) (1984): Sensory Processes, Vol. III, Parts 1 and 2
Plum F. (ed) (1987): Higher Functions of the Brain, Vol. V, Parts 1 and 2

Hanson A.R., Riseman E. (ed): (1978) Computer Vision Systems. Academic Press, New York

Hanson A.R., Riseman E. (1987): The VISIONS image understanding system – 1986. In: Brown C (ed) Advances in Computer Vision. Erlbaum, Hillsdale, NJ

Haralick R.M., Shapiro L.G. (1993): Computer and Robot Vision. Addison–Wesley

Harel D. (1987): State charts: A Visual Formalism for Complex Systems. Science of Computer Programming, 8: 231–274

Harris C.G., Stephens M. (1988): A combined corner and edge detector. Proc. 4th Alvey Vision Conf.: 147-151

Hillis W.D. (1992) (6th printing): The Connection Machine. MIT Press, Cambridge, MA

Hock C., Behringer R., Thomanek F. (1994): Intelligent Navigation for a Seeing Road Vehicle using Landmark Recognition. In: Close Range Techniques and Machine Vision. ISPBS, Melbourne Australia

Hock C. (1994): Wissensbasierte Fahrzeugfuehrung mit Landmarken fuer autonorne Roboter. Diss., UniBw Munich, LRT

Hofmann U., Dickmanns E.D. (2000): EMS-Vision: An Application to Intelligent Cruise Control for High Speed Roads. Proceedings International Symposium on Intelligent Vehicles, Dearborn, MI: 468–473

Hofmann U., Rieder A., Dickmanns E.D. (2003): Radar and Vision Data Fusion for Hybrid Adaptive Cruise Control on Highways. Journal of Machine Vision and Application, 14(1): 42–49

Hofmann U. (2004): Zur visuellen Umfeldwahrnehmung autonomer Fahrzeuge. Diss., UniBw Munich, LRT

Hogg D.C. (1984): Interpreting images of a known moving object. Ph.D. thesis, University of Sussex, Department of Computer Science

http://iris.usc.edu/Vision-Notes/bibliography/contents.html

Hubel D.H., Wiesel T. (1962): Receptive fields, binocular interaction, and functional architecture in the cat's visual cortex. Journal of Physiology, 160: 106–154

IV'00 (2000): Proceedings of the International Symposium on Intelligent Vehicles. Dearborn, MI, with the following contributions on EMS-Vision: Gregor *et al*. (2000a, b), Hofmann *et al*. (2000), Lützeler *et al*. (2000), Maurer (2000), Pellkofer *et al*. (2000), Siedersberger (2000), [*individual references under these names*]

Jaynes E.T. (2003): Probability Theory, The Logic of Science. Cambridge Univ. Press

Johansson G. (1973): Visual perception of biological motion and a model for its analysis. Perception and Psychophysics 14(2): 201–211

Kailath T. (1980): Linear Systems. Prentice-Hall Inc., Englewood Cliffs, NJ

Kailath T., Sayed A.H., Hassibi B. (2000): Linear estimation. Prentice Hall Inc., Englewood Cliffs, NJ

Kalinke T., Tzomkas C., v. Seelen W. (1998): A Texture-based Object Detection and an Adaptive Model-based Classification. Proceedings International Symposium on Intelligent Vehicles'98, Stuttgart

Kalman R.D. (1960) A new approach to linear filtering and prediction problems. Trans. ASME, Series D, Journal of Basic Engineering: 35–45

Kalman R.D., Bucy R.S. (1961) New results in linear filtering and prediction theory. Trans. ASME, Series D, Journal of Basic Engineering: 95–108.

Kanade T. (ed,) (1987): Three-Dimensional Machine Vision. Kluwer Acad. Publ.

Kenue S. (1989): Lanelok: Detection of lane boundaries and vehicle tracking using image processing techniques: Parts I and II. In: SPIE Proc. Mobile Robots

Kinzel W. (1994a): Pedestrian Recognition by Modeling their Shapes and Movements. In S. Impedovo (ed.) (1994) Progress in Image Analysis and Processing III; Proc. 7th Int. Conf. on Image Analysis and Processing, IAPR, World Scientific, Singapore: 547–554

Kinzel W. (1994b): Präattentive und attentive Bildverarbeitungsschritte zur visuellen Erkennung von Fußgängern. Diss., UniBw Munich, LRT. Also as Fortschrittsberichte VDI Verlag, Reihe 10, Nr. 329

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

Kluge K., Thorpe C. (1988): Explicit models for robot road following. In: Proc. IEEE Conf. on Robotics and Automation

Koch C. (1995): Vision Chips: Implementing Vision Algorithms with Analog VLSI Circuits. IEEE Computer Society Press

Koenderink J.J., van Doorn A.J. (1990): Receptive field families. Biol.Cybern., 63: 291–298

Koller D., Daniilidis K., Nagel H.H. (1993): Model-based object tracking in monocular image sequences of road traffic scenes. Int. J. of Computer Vision, 3(10): 257–281

Kraft H., Frey J., Moeller T., Albrecht M., Grothof M., Schink B., Hess H., Buxbaum B. (2004): 3D-Camera of High 3D-Frame Rate, Depth-Resolution and Background Light Elimination Based on Improved PMD (Photonic Mixer Device) –Technologies. OPTO 2004, AMA Fachverband, Nuremberg, Germany

Kroemer K.H.E. (1988): Ergonomic models of anthropomorphy, human biomechanics, and operator-equipment interfaces. Proc. of a Workshop, Committee on Human Factors, National Academy Press, Washington DC: 114–120

Kuan D., Phipps G., Hsueh A.C. (1986): A real time road following vision system for autonomous vehicles. Proc. SPIE Mobile Robots Conf., 727, Cambridge MA: 152–160

Kuehnle A. (1991): Symmetry-based recognition of vehicle rears. In: Pattern Recognition Letters 12 North-Holland: 249–258

Kuhnert K.D. (1988): Zur Echtzeit-Bildfolgenanalyse mit Vorwissen. Diss. UniBw Munich, LRT

Kujawski D. (1995): Deciding the Behaviour of an Autonomous Road Vehicle in Complex Traffic Situations. 2nd IFAC Conf. on Intelligent Autonomous Vehicles-95, Helsinki

Labayarde R., Aubert D., Tarel P. (2002): Real Time Obstacle Detection in Stereovision on non Flat Road Geometry through ‘V-disparity’ representation. Proceedings International Symposium on Intelligent Vehicles’02, Versailles

Leonhard J.J., Durrant-White H.F. (1991): Mobile robot localization by tracking geometric beacons. IEEE Transactions on Robotics and Automation 7: 376–382

Loffeld O. (1990): Estimationstheorie. Oldenbourg

Luenberger D.G. (1964): Observing the state of a linear system. IEEE Trans. on Military Electronics 8: 74–80

Luenberger D.G. (1964): Observing the state of a linear system. IEEE Trans. on Military Electronics 8: 290–293.

Luenberger D.G. (1966): Observers for Multivariable Systems. IEEE Trans. Automatic Control, AC-11: 190–197

Lützeler M., Dickmanns E.D. (2000): EMS-Vision: Recognition of Intersections on Unmarked Road Networks. Proceedings International Symposium on Intelligent Vehicles, Dearborn, MI: 302–307

Lützeler M. (2002): Fahrbahnerkennung zum Manoevrieren auf Wegenetzen mit aktivem Sehen. Diss. UniBw Munich, LRT. Also as Fortschrittsberichte VDI Verlag, Reihe 12, Nr. 493

Mandelbaum R., Hansen M., Burt P., Baten S. (1998): Vision for Autonomous Mobility: Image Processing on the VFE-200. In: IEEE International Symposium on ISIC, CIRA and ISAS

Marr D., Nishihara H.K. (1978): Representation and Recognition of the spatial organization of three-dimensional shape. Proceedings of the Royal Society of London, Series B 200: 269–294

Marr D (1982): Vision. W.H. Freeman, New York

Marshall S (1989): Review of shape coding techniques. Image and Vision Computing, 7(4): 281–294

Masaki I. (1992++): yearly ‘International Symposium on Intelligent Vehicles’, in later years appearing under IEEE – ITSC sponsorship. Proceedings

Maurer M. (2000): Knowledge Representation for Flexible Automation of Land Vehicles. Proc. of the International Symposium on Intelligent Vehicles, Dearborn, MI: 575–580

Maurer M. (2000): Flexible Automatisierung von Strassenfahrzeugen mit Rechnersehen. Diss. UniBw Munich, LRT. Also as Fortschrittsberichte VDI Verlag, Reihe 12, Nr. 443

Maurer M. , Stiller C. (2005): Fahrerassistenzsysteme mit maschineller Wahrnehmung. Springer, Berlin

Maybeck. PS (1979): Stochastic models, estimation and control. Vol. 1, Academic Press, New York

Maybeck P.S. (1990): The Kalman filter: An introduction to concepts. In: Cox, I.J., Wilfong G.T. (eds): Autonomous Robot Vehicles, Springer–Verlag

McCarthy J. (1955): Making Robots Conscious of their Mental State. Computer Science Report, Stanford University, CA

McCarthy J., Minsky M., Rochester N., Shannon C. (1955): A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence, Aug. 31

Meissner H.G. (1982): Steuerung dynamischer Systeme aufgrund bildhafter Informationen. Diss., UniBw Munich, LRT

Meissner H.G., Dickmanns E.D. (1983): Control of an Unstable Plant by Computer Vision. In: Huang T.S. (ed) (1983): Image Sequence Processing and Dynamic Scene Analysis. Springer-Verlag, Berlin: 532–548

Metaxas D.N., Terzopoulos D. (1993): Shape and Nonrigid Motion Estimation Through Physics-Based Synthesis. IEEE Trans. Pattern Analysis and Machine Intelligence 15(6): 580–591

Mezger W. (1975, 3. Auflage): Gesetze des Sehens. Verlag Waldemar Kramer, Frankfurt M. (1. Auflage 1936, 2. Auflage 1953)

Miller G., Galanter E., Pribram K. (1960): Plans and the Structure of Behavior. Holt, Rinehart & Winston, New York

Mitschke M. (1988): Dynamik der Kraftfahrzeuge – Band A: Antrieb und Bremsung. Springer-Verlag, Berlin, Heidelberg, New York, London, Tokio

Mitschke M. (1990): Dynamik der Kraftfahrzeuge - Band C: Fahrverhalten. Springer-Verlag, Berlin, Heidelberg, New York, London, Tokio

Moravec H. (1979): Visual Mapping by a Robot Rover. Proc. IJCAI 1079: 598–600

Moravec H. (1983): The Stanford Cart and the CME Rover. PIEEE(71), 7: 872–884

Mori H., Charkari N.M. (1993): Shadow and rhythm as sign patterns of obstacle detection. In IEEE Int. Symp. on Industrial Electronics, Budapest: 271–277

Moutarlier, P. Chatila R. (1989): Stochastic multisensory data fusion for mobile robot location and environment modeling. In: 5th International Symposium on Robotic Research, Tokyo.

Müller N., Baten S. (1995): Image Processing Based Navigation with an Autonomous Car. International Conference on Intelligent Autonomous Systems (IAS–4), Karlsruhe: 591–598

Müller N. (1996): Autonomes Manoevrieren und Navigieren mit einem sehenden Strassenfahrzeug. Diss., UniBw Munich, LRT. Also as Fortschrittsberichte VDI Verlag, Reihe 12, Nr. 281

Mysliwetz B, Dickmanns E.D. (1986) A Vision System with Active Gaze Control for real-time Interpretation of Well Structured Dynamic Scenes. In: Hertzberger LO (ed) (1986) Proceedings of the First Conference on Intelligent Autonomous Systems (IAS-1), Amsterdam: 477–483

Mysliwetz B. (1990): Parallelrechner–basierte Bildfolgen–Interpretation zur autonomen Fahrzeugsteuerung. Diss., UniBw Munich, LRT

Nevatia R., Binford T. (1977): Description and recognition of curved objects. Artificial Intelligence, 8: 77–98

Newell A., Simon H. (1963): GPS: a program that simulates human thought. In: Feigenbaum E., Feldman J. (eds): Computers and Thought. McGraw-Hill, New York

Nieuwenhuis S., Yeung N. (2005): Neural mechanisms of attention and control: losing our inhibitions? Nature Neuroscience, 8 (12): 1631–1633

Nilsson N.J. (1969): A Mobile Automaton: An Application of Artificial Intelligence. Proceedings International Joint Conference on Artificial Intelligence (IJCAI): 509–521

Nishimura M., Van der Spiegel J. (2003): Biologically Inspired Vision Sensor for the Detection of Higher–Level Image Features. Proc. IEEE Conf. on Electron Devices and Solid-State Circuits: 11–16

Nunes J.C., Guyot S., Delechelle E. (2005): Texture analysis based on local analysis of the Bidimensional Empirical Mode Decomposition. J. Machine Vision and Application, 16: 177–188

Paetzold F., Franke U. (2000): Road recognition in urban environment. Image and vision Computing 18(5): 377–387

Papoulis A. (1962):The Fourier Integral and Its Applications. McGraw-Hill, New York

Pele S., Rom H. (1990): Motion based segmentation. In: Proc. IEEE Int. Conf. Pattern Recognition, Atlantic City: 109–113

Pellkofer M., Dickmanns E.D. (2000): EMS–Vision: Gaze Control in Autonomous Vehicles. Proceedings International Symposium on Intelligent Vehicles'00, Dearborn, MI: 296–301

Pellkofer M., Lützeler M., Dickmanns E.D. (2001): Interaction of Perception and Gaze Control in Autonomous Vehicles. Proc. SPIE: Intelligent Robots and Computer Vision XX, Newton: 1–12

Pellkofer M., Dickmanns E.D. (2002): Behavior Decision in Autonomous Vehicles. Proceedings International Symposium on Intelligent Vehicles'02, Versailles

Pellkofer M. (2003): Verhaltensentscheidung für autonome Fahrzeuge mit Blickrichtungssteuerung. Diss., UniBw Munich, LRT

Pellkofer M., Lützeler M., Dickmanns E.D. (2003): Vertebrate-type perception and gaze control for road vehicles. In: Jarvis R.A., Zelinski A.: Robotics Research. The Tenth International Symposium, Springer–Verlag: 271–288

Pellkofer M., Hofmann U., Dickmanns E.D. (2003): Autonomous cross-country driving using active vision. SPIE Conf. 5267, Intelligent Robots and Computer Vision XXI: Algorithms, Techniques and Active Vision. Photonics East, Providence

PMDTech (2006): See: Kraft *et al*. (2004)

Pöppel E., Chen L., Glünder H., Mitzdorf U., Ruhnau E., Schill K., von Steinbüchel N. (1991): Temporal and spatial constraints for mental modelling. In: Bhatkar, Rege K (eds): Frontiers in knowledge-based computing, Narosa, New Dehli: 57–69

Pöppel E. (1994): Temporal Mechanisms in Perception. International Review of Neurobiology, 37: 185–202

Pöppel E., Schill K. (1995): Time perception: problems of representation and processing. In: Arbib M.A. (ed): The handbook of brain theory and neural networks, MIT Press, Cambridge: 987–990

Pöppel E. (1997): A hierarchical model of temporal perception. Trends in Cognitive Science, Vol.1 (2)

Pomerleau D.A. (1989) ALVINN: An Autonomous Land Vehicle in Neural Network. In: Touretzky D.S. (ed): Advances in Neural Information Processing Systems 1. Morgan Kaufmann,

Pomerleau D.A. (1992): Neural Network Perception for Mobile Robot Guidance. PhD-thesis, CMU, Pittsburgh [CMU-CS-92-1l5]

Potter J.E. (1964): W Matrix Augmentation. MIT Instrumentation Laboratory Memo SGA 5-64 Cambridge MA

Priese L, Lakmann R, Rehrmann V (1995): Ideogram Identification in a Realtime Traffic Sign Recognition System. Proc. Int. Symp. on Intelligent Vehicles, Detroit: 310–314

RAS-L-1 (1984): Richtlinien fuer die Anlage von Strassen (RAS). Forschungsgesellschaft fuer Strassen- und Verkehrswesen (ed.), Cologne, Germany, edition 1984. [Guide lines for the design of roads]

Rasmussen C. (2002): Combining Laser Range, Color, and Texture Cues for Automated Road Following. Proc. IEEE International Conference on Robotics and Automation, Washington DC

Regensburger U., Graefe V. (1990): Object Classification for Obstacle Avoidance. Proc. of the SPIE Symposium on Advances in Intelligent Systems, Boston: 112–119

Regensburger U. (1993): Zur Erkennung von Hindernissen in der Bahn eines Strassenfahrzeugs durch maschinelles Echtzeitsehen. Diss., UniBw Munich, LRT

Rieder A. (1996): Trinocular Divergent Stereo Vision. Proc. 13th International Conference on Pattern Recognition (ICPR) Vienna: 859–863

Rieder A. (2000): FAHRZEUGE SEHEN – Multisensorielle Fahrzeugerkennung in einem verteilten Rechnersystem fuer autonome Fahrzeuge. Diss. UniBw Munich, LRT

Ritter W. (1997): Automatische Verkehrszeichenerkennung. Koblenzer Schriften zur Informatik, Band 5, Verlag D. Fölbach, Diss., Univ. Koblenz/Landau

Roberts L.G. (1965): Homogeneous matrix representation and manipulation of n-dimensional constructs. MS-1405, Lincoln Laboratory, MIT

Roland A., Shiman P. (2002): Strategic Computing: DARPA and the Quest for Machine Intelligence, 1983–1993. MIT Press

Rosenfeld A., Kak A. (1976): Digital Picture Processing, Academic Press, New York

Ruhnau E. (1994a) The Now – A hidden window to dynamics. In Atmanspacher A, Dalenoort G.J. (eds): Inside versus outside. Endo- and Exo-Concepts of Observation and Knowledge in Physics, Philosophy and Cognitive Science, Springer, Berlin

Ruhnau E. (1994b): The Now – The missing link between matter and mind. In Bitbol M, Ruhnau E. (eds): The Now, Time and Quantum. Gif-sur-Yvette: Edition Frontière

Sack A.T., Kohler A., Linden D.E., Goebel R., Muckli L. (2006): The temporal characteristics of motion processing in hMT/V5+: Combining fMRI and neuronavigated TMS Neuroimage, 29: 1326–1335

Schick J., Dickmanns E.D. (1991): Simultaneous Estimation of 3-D Shape and Motion of Objects by Computer Vision. In Proc. IEEE Workshop on Visual Motion, Princeton, NJ, IEEE Computer Society Press: 256–261

Schick J. (1992): Gleichzeitige Erkennung von Form und Bewegung durch Rechnersehen. Diss., UniBw Munich, LRT

Schiehlen J. (1995): Kameraplattformen fuer aktiv sehende Fahrzeuge. Diss., UniBw Munich, LRT. Also as Fortschrittsberichte VDI Verlag, Reihe 8, Nr. 514

Schmid M., Thomanek F. (1993): Real-time detection and recognition of vehicles for an autonomous guidance and control system. Pattern Recognition and Image Analysis 3(3): 377–380

Schmid M.(1993): 3-D-Erkennung von Fahrzeugen in Echtzeit aus monokularen Bildfolgen. Diss. UniBw Munich, LRT. Also as Fortschrittsberichte VDI Verlag, Reihe 10, Nr. 293

Scudder M., Weems C.C. (1990): An Apply Compiler for the CAAPP. Tech. Rep. UM-CS-1990-060, University of Massachusetts, Amherst

Selfridge O., (1959): Pandemonium: A paradigm for learning. In: The Mechanization of Thought Processes. Her Majesty's Stationary Office, London

Selfridge O., Neisser U., (1960): Pattern Recognition by Machine. Scientific American, 203: 60–68

Shirai Y. (1987): Three Dimensional Computer Vision. Series Symbolic Computation, Springer, Berlin

Siedersberger K.-H. (2000): EMS-Vision: Enhanced Abilities for Locomotion. Proceedings International Symposium on Intelligent Vehicles'00), Dearborn, MI: 146–151

Siedersberger K.H., Pellkofer M., Lützeler M., Dickmanns E.D., Rieder A., Mandelbaum R., Bogoni I., (2001): Combining EMS-Vision and Horopter Stereo for Obstacle Avoidance of Autonomous Vehicles. Proc. ICVS, Vancouver

Siedersberger K.H. (2004): Komponenten zur automatischen Fahrzeugführung in sehenden (semi-) autonomen Fahrzeugen. Diss., UniBw Munich, LRT

Solder U., Graefe V. (1990): Object Detection in Real Time. Proc. of the SPIE, Symp. on Advances in Intelligent Systems, Boston: 104–111

Spillmann W. (1990) Visual Perception. The Neurophysiological Foundations. Academic Press, New York

Spivak M. (1970): A Comprehensive Introduction to Differential Geometry. (Volumes I – V). Publish or Perish, Berkeley, CA

Steels L. (1993): The Biology and Technology of Intelligent Autonomous Agents. NATO-Advanced Study Institute. Ivano, Italy

Talati A., Hirsch J. (2005): Functional specialization within the medial frontal gyrus for perceptual "go/no-go" decisions based on "what", "when", and "where" related information: an fMRI study. Journal of Cognitive Neuroscience, 17(7): 981–993

Talati A., Valero-Cuevas F.J., Hirsch J. (2005): Visual and Tactile Guidance of Dexterous Manipulation: an fMRI Study. Perceptual and Motor Skills, 101: 317–334

Thomanek F., Dickmanns D. (1992): Obstacle Detection, Tracking and State Estimation for Autonomous Road Vehicle Guidance. In: Proc. of the 1992 International Conference on Intelligent Robots and Systems, Raleigh NC, IEEE, SAE: 1399–1407

Thomanek F., Dickmanns E.D., Dickmanns D. (1994): Multiple Object Recognition and Scene Interpretation for Autonomous Road Vehicle Guidance. In: Masaki I. (ed): Proc. of International Symposium on Intelligent Vehicles '94, Paris: 231–236

Thomanek F. (1996): Visuelle Erkennung und Zustandsschätzung von mehreren Straßenfahrzeugen zur autonomen Fahrzeugführung. Diss., UniBw Munich, LRT. Also as Fortschrittsberichte VDI Verlag, Reihe 12, Nr. 272

Thornton C.L., Bierman G.J. (1977): Gram-Schmidt Algorithms for Covariance Propagation. International Journal of Control 25(2): 243–260

Thornton C.L., Bierman G.J. (1980): UDU^T Covariance Factorization for Kalman Filtering. In: Control and Dynamic Systems, Advances in Theory and Application, Vol. 16, Academic Press, New York: 178–248

Thorpe C., Hebert M., Kanade T., Shafer S. (1987): Vision and navigation for the CMU Navlab. Annual Review of Computer Science, Vol. 2

Thorpe C., Kanade T. (1986): Vision and Navigation for the CMU Navlab. In: SPIE Conf. 727 on 'Mobile Robots', Cambridge, MA

Thrun S., Burgard W., Fox D. (2005): Probabilistic Robotics. MIT Press, Cambridge, MA

Tomasi C., Kanade T. (1991): Detection and Tracking of Point Features. CMU, Tech. Rep. CMU-CS-91-132, Pittsburgh, PA

Tsinas L. (1996): Zur Auswertung von Farbinformationbeim maschinellen Erkennen von Verkehrssituationen in Echtzeit. Diss., UniBw Munich, LRT

Tsugawa S., Yatabe T., Hirose T., Matsumoto S. (1979): An Automobile with Artificial Intelligence. Proc. 6th IJCAI, Tokyo: 893-895

Tsugawa S., Sadayuki S. (1994): Vision-based vehicles in Japan: Machine vision systems and driving control systems. IEEE Trans. Industrial Electronics 41(4): 398–405

Turk M.A., Morgenthaler D.G., Grembran K.D., Marra M. (1987): Video road-following for the autonomous land vehicle. Proc. IEEE Int. Conf. Robotics and Automation, Raleigh, NC: 273–280

Ulmer B. (1994): VITA II - Active collision avoidance in real traffic. Proceedings International Symposium on Intelligent Vehicles'94, Paris

von Holt V. (1994): Tracking and classification of overtaking vehicles on Autobahnen. Proceedings International Symposium on Intelligent Vehicles'94, Paris

von Holt V. (2004): Integrale Multisensorielle Fahrumgebungserfassung nach dem 4-D Ansatz. Diss. UniBw Munich, LRT

Wallace R., Stentz A., Thorpe C., Moravec H., Wittaker W., Kanade T. (1985) First Results in Robot Road-Following. Proc. 9^{th} IJCAI: 65–67

Wallace R., Matsusaki K., Goto S., Crisman J., Webb J., Kanade T. (1986): Progress in Robot Road-Following. Proceedings International Conference on Robotics and Automation, San Francisco CA: 1615–1621

Werner S. (1997): Maschinelle Wahrnehmung fuer den bordautonomen automatischen Hubschrauberflug. Diss. UniBw Munich, LRT

Wertheimer M. (1921): Untersuchungen zur Lehre der Gestalt I. Psychol. Forschung, Bd 1

Wiener N. (1948) Cybernetics. Wiley, New York

Winograd T., Flores C.F. (1990): Understanding Computers and Cognition. A New Foundation for Design. Addison-Wesley

Wünsche H.J. (1983): Verbesserte Regelung eines dynamischen Systems durch Auswertung redundanter Sichtinformation unter Berücksichtigung der Einflüsse verschiedener Zustandsschätzer und Abtastzeiten. Report HSBw/LRT/WE 13a/IB/83-2

Wünsche H.J. (1986): Detection and Control of Mobile Robot Motion by Real-Time Computer Vision. In: Marquino N. (ed): Advances in Intelligent Robotics Systems. Proc. SPIE, 727: 100–109

Wünsche H.J. (1987): Bewegungssteuerung durch Rechnersehen. Diss. UniBw Munich, LRT. Also as Fachberichte Messen, Steuern, Regeln Bd. 10, Springer-Verlag, Berlin, 1988

Zapp A. (1988): Automatische Straßenfahrzeugführung durch Rechnersehen, Diss., UniBw Munich, LRT

Zheng Y.J., Ritter W., Janssen R. (1994): An adaptive system for traffic sign recognition. Proc. Int. Symp. on Intelligent Vehicles, Paris

Zielke T., Brauckmann M., von Seelen W. (1993): Intensity and Edge-based Symmetry Detection with an Application to Car Following. CGVIP: Image Understanding 58: 177–190

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