Scene Interpretation and Behavior Planning for Driver Assistance

U. Handmann, I. Leefken and W. v.Seelen

Institut für Neuroinformatik
Lehrstuhl für theoretische Biologie
Ruhr-Universität Bochum
44780 Bochum, Germany

ABSTRACT

The scene interpretation and the behavior planning of a vehicle in real world traffic is a difficult problem to be solved. If different hierarchies of tasks and purposes are built to structure the behavior of a driver, complex systems can be designed. But finally behavior planning in vehicles can only influence the controlled variables: steering angle and velocity. In this paper a scene interpretation and a behavior planning for a driver assistance system aiming on cruise control is proposed. In this system the controlled variables are determined by an evaluation of the dynamics of a two-dimensional neural field for scene interpretation and two one-dimensional neural fields controlling steering angle and velocity. The stimuli of the fields are determined according to the sensor information.

Keywords: Driver Assistance, Intelligent Vehicles, Neural Field Dynamics

1. INTRODUCTION

Driver assistance systems have to assist the driver of a vehicle in his actions. The degree of the complexity of such systems can vary from information proposed to the driver[1] to almost autonomous driving.[2–4] For the given purpose the generated behavior-advice or action is determined by the actual task, the safety- and the comfort-considerations. Those constraints combined with the information about the environment build the basis of the scene interpretation and the behavior planning part of a driver assistance system. The information about the environment is gained from sensor data, knowledge and integration over time.

In the scene interpretation task the incoming data (in sensor coordinates) are transformed to a common description base. Actually object- and lane-information are transformed to world coordinates with respect to the moving observer. The positions of the detected objects are determined in a bird's-eye view of the driving plane. This representation is organized dynamically using a neural field[5,6] for stabilization of data and interpretation of the constellation of the given objects for the scene analysis. The behavior planning task has to be made up of a set of basic behaviors (e.g. tracking of a leader, driving backwards) or, if no adequate basic behavior is known in advance, by calculating a dynamic transition of the controlled values for the behavior planning. In the presented paper the dynamics for behavior planning are formulated in the coordinates of the controlled values of the vehicle. The steering angle and the velocity are controlled using two one-dimensional neural fields.[7]

In the presented paper first a short introduction to the architecture in which the scene interpretation and the behavior planning are embedded is given. Then the theoretical approach to neural field dynamics and the properties of the dynamics in the one- and two-dimensional case are provided. Afterwards the structure of the scene interpretation and the considerations of the behavior planning are introduced. The paper is completed by the presentation of results based on real data as well as on simulation results and by conclusions.

Correspondence:
I. Leefken: E-mail: Iris.Leefken@neuroinformatik.ruhr-uni-bochum.de
U. Handmann: E-mail: Uwe.Handmann@neuroinformatik.ruhr-uni-bochum.de
W. v.Seelen: E-mail: institut@neuroinformatik.ruhr-uni-bochum.de

2. ARCHITECTURE

In this section a coarse description of the flexible and modular architecture of the driver assistance system is given (fig. 1). For a closer look the reader is refered to.[8]

- In the given architecture the environment of the vehicle is perceived by different sensors like vision-, radar- or lidar-sensors.
- The sensor information is analyzed sensor based in the object-related analysis to achieve the optimal result for each sensor. In this part object hypotheses are generated by fusion of different sensor data, segmentation, tracking and classification modules.[9,10]
- In the scene interpretation part the object hypotheses are incorporated into a common coordinate system and evaluated according to given knowledge (e.g., physical laws, traffic rules). A stabilization over time and an analysis of the scene is done to provide information to the dynamic part of the knowledge base on a large time scale. The information concerning relevant objects of the scene are passed to the behavior planning.
- In the behavior planning part of the architecture decisions for the needed behavior are made. The decisions are based on the dynamic coupling of scene information, actual task specifications and knowledge (e.g. lane-information). The results of the behavior planning can either result in actions (section 5) or in behavior advices.[11]
- The knowledge base is divided into static, external and dynamic knowledge to regard the different types of information stored in the system. Static knowledge is not changing over time like traffic or physical rules which are known previously to the system. Dynamic knowledge is changing over time, like lane-information, information about the actual situation or large time-scale developments and states (e.g. driving on a freeway). External knowledge is acquired from onboard receivers like a GPS-receiver based on which a road-estimation can be generated or stabilized.

The architecture is organized flexible and modular to enable the separate introduction of its elements. In this paper we concentrate on the dynamics of the scene interpretation and the behavior planning. In the following section the theory for neural field dynamics which is applied for both modules is presented.

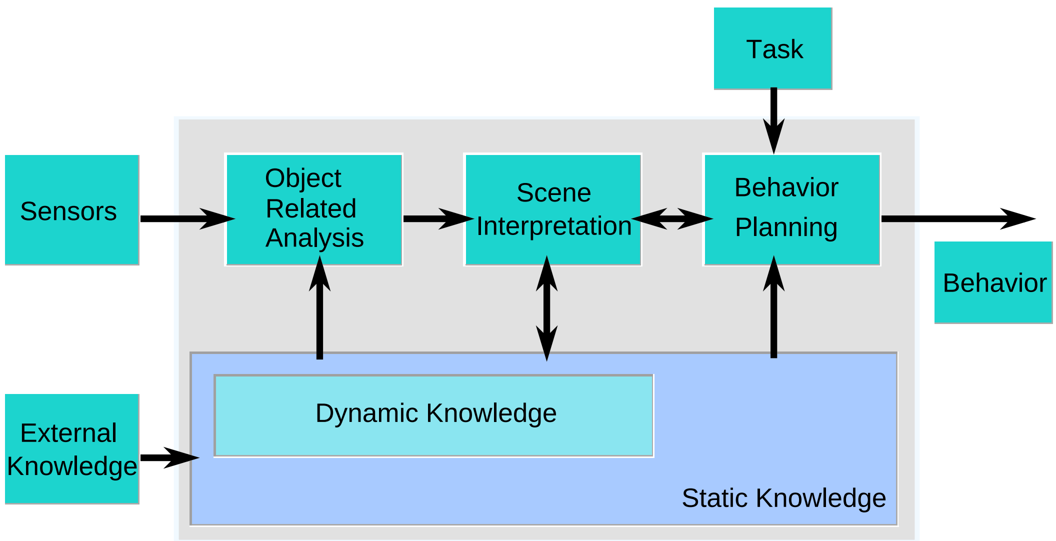


Figure 1. Architecture for a driver assistance system.

3. NEURAL FIELD DYNAMICS

In this section a description of the theory of neural field dynamics is given. Neural fields are used to organize the scene interpretation and the behavior planning part of the driver assistance system.

Neural fields are nonlinear dynamic systems. Originally they were introduced as models of the neurophysiology of cortical processes. The chosen realization of a neural field was introduced in[7] and extended to multi-dimensional fields in.[5,6] The dynamic properties of this approach have been examined extensively. Further information on one- and two-dimensional fields can be found in.[7,12,6]

The field equation of an n-dimensional neural field is given by

$$\tau\dot{u}(\mathbf{z},t) = -u(\mathbf{z},t) + h + S(\mathbf{z},t) + \int_\Gamma w(\mathbf{z},\mathbf{z}')\varphi(u(\mathbf{z}',t))d\mathbf{z}' \quad , \tag{1}$$

where $u(\mathbf{z},t)$ is the field excitation at time $t(t \geq 0)$ at the position $\mathbf{z} \in \mathbb{R}^n$. The position $\mathbf{z}$ characterizes the position of the field-site relative to a reference position $\mathbf{z} = \mathbf{0}$. The temporal derivative of the excitation is defined by

$$\dot{u}(\mathbf{z},t) = \frac{\partial u(\mathbf{z},t)}{\partial t}.$$

The excitation $u(\mathbf{z},t)$ of the field varies with the time constant τ with $\tau \in \mathbb{R}^+$. By means of the parameter h a constant preactivation of the field is achieved. The stimulus $S(\mathbf{z},t) \in \mathbb{R}$ represents the input of the field which is dependent on the field position and varies with time. A nonlinear interaction between the excitation $u(\mathbf{z},t)$ of one field-site at position $\mathbf{z}$ and the excitation of its neighboring field-sites at positions $\mathbf{z}'$ is achieved by the convolution of an interaction kernel $w(\mathbf{z},\mathbf{z}') = w(\mathbf{z}-\mathbf{z}')$ and a nonlinear activation function $\varphi(u(\mathbf{z}',t))$. The integration is performed over the set Γ of all field-sites. To guarantee the stability of the solution the activation function is supposed to have a continuous derivative and the properties

$$\lim_{u\to-\infty}\varphi(u) = 0 \quad \wedge \quad \lim_{u\to\infty}\varphi(u) = 1 \qquad .$$

The interaction kernel is chosen adequately to the intention of diffusion or concentration of the actual field activation. Mostly Gaussian functions (diffusion),

$$f_G(\mathbf{z}) = c_0 \cdot e^{-\sum_{i=1}^{n}(\frac{z_i^2}{2\sigma_{0,i}^2})}, \quad \mathbf{z} = [z_1, \cdots z_i, \cdots, z_n]^T,$$

or Mexican Hat functions (concentration),

$$f_{MH}(\mathbf{z}) = c_0 \cdot e^{-\sum_{i=1}^{n}(\frac{z_i^2}{2\sigma_{0,i}^2})} - c_1 \cdot e^{-\sum_{i=1}^{n}(\frac{z_i^2}{2\sigma_{1,i}^2})}, \quad \mathbf{z} = [z_1, \cdots z_i, \cdots, z_n]^T,$$

are applied.

For the scene-interpretation a two-dimensional neural field is chosen representing the bird's-eye view of sensed scene, while for the behavior planning a one-dimensional field coding the change in steering angle and the velocity is applied.

3.1. One-dimensional field

The one-dimensional field is defined as shown in eq. 1 for $\mathbf{z} = z \in \mathbb{R}^1$. The equilibrium solutions

$$\lim_{t\to\infty} u(z) \qquad \text{with} \qquad \frac{\partial S(z,t)}{\partial t} = const. \quad \forall t > t_0$$

for the one-dimensional field are divided into three categories[7]:

1. $\emptyset$-solution, if $u(z,t) \leq 0 \quad \forall z \in \Gamma$
2. ∞-solution, if $u(z,t) > 0 \quad \forall z \in \Gamma$
3. a-solutions, if local restricted excitations $R(u) = (z_1, z_2)$ of the length $a = z_2 - z_1$ occur.

The excitation $R(u)$ is defined by

$$R(u) = \{z|u(z) > 0 \quad \forall z \in]z_1, z_2[\wedge u(z_1) = u(z_2) = 0\} \qquad .$$

If only one a-solution exists the solution is called a single-peak or mono-modal solution, if several a-solutions exist a multi-peak or multi-modal solution is given.

In case of a driver assistance task a single-peak solution is favorable as only one steering angle or one change in velocity can be set at one time step.

The type of solution is dependent on the stimulus, the preactivation h and the interaction-kernel $w(z)$. According to Amari[7] the correct choice of the parameters of the preactivation and the interaction enables the existence of single-peak and multi-peak solutions. Therefore it must be fulfilled, that

$$W(a) + h = 0 \tag{2}$$

$$h < 0 \tag{3}$$

and

$$W(a) = \int_{z_1}^{z_2} w(z)dz \quad .$$

For two-dimensional neural fields the proofs for robustness and stability are different but similar properties apply, which are described in the next subsection.

3.2. Two-dimensional neural field

In case of a two-dimensional field Taylor[6] has shown that the types of solutions as well as eq. 2 and 3 can be determined in a similar way. The equilibrium solutions are defined similar to the solutions of one-dimensional neural fields shown in 3.1. The definition of a local excitation in a two-dimensional neural field is defined by

$$R(u) = \{\mathbf{z}|u(\mathbf{z}) > 0 \quad \forall \mathbf{z} \in D/\partial D \wedge u(\mathbf{z} \in \partial D) = 00\} \qquad ,$$

with D defining a convex manifold in $\mathbb{R}^2$ in which $u(\mathbf{z}, t) > 0$ and ∂D defining the boundary of D. For the two-dimensional field describing object-positions a $\emptyset$-solution is desired if there is no stationary input. If there is a constant input for a long period of time an a-solution is required.

The main advantage of the Amari-field is the additive composition of the stimulus. The field can be stimulated starting with less information which can be additively broadened as more relevant information is obtained and is formulated in terms of the field-variable z. The data for the field stimulus have to be coded adequately with respect to the effect they are supposed to have on the field activation (e.g. negative values for inhibition of regions, positive values for excitation).

4. SCENE INTERPRETATION

The scene interpretation interprets and integrates object hypotheses gained from different sensors in order to extract consistent, task-relevant information. The scene interpretation is subdivided into a behavior-based representational and a scene analysis part (fig. 2).

In the representational part the object hypotheses are evaluated using knowledge and neural field dynamics. The scene analysis interprets the constellation of detected objects and generates information describing the scene. In this paper we concentrate on the representational part as the generated information already can by used for behavior planning.

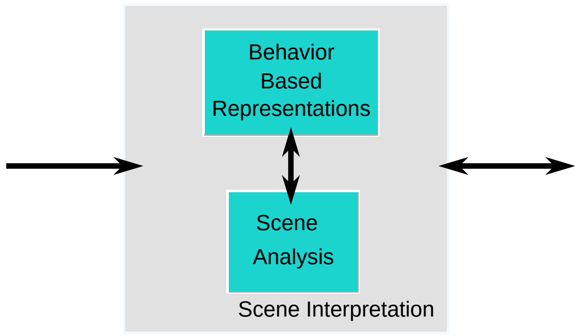


Figure 2. Structure of the scene interpretation.

4.1. Representation

The representation is used to decide which object hypotheses have to be accepted. It is subdivided into four different modules: the data integration, the knowledge integration, the dynamics and the internal memory.

In the data integration module the object hypotheses (fig. 3) described in sensor-coordinates are integrated for different logical sensors* and transformed to a common description base for all sensors. The integration of object hypotheses for different logical sensors is performed to overcome redundant information gained from different algorithms. Hypotheses describing the same object are fused. On base of the results of the data integration a knowledge based evaluation and integration of the object hypotheses can be performed. This is done in the knowledge integration. In this module knowledge (e.g. physical rules) is applied to evaluate object hypotheses concerning consistency considerations. The extracted object hypotheses are passed to the dynamics of the representation.

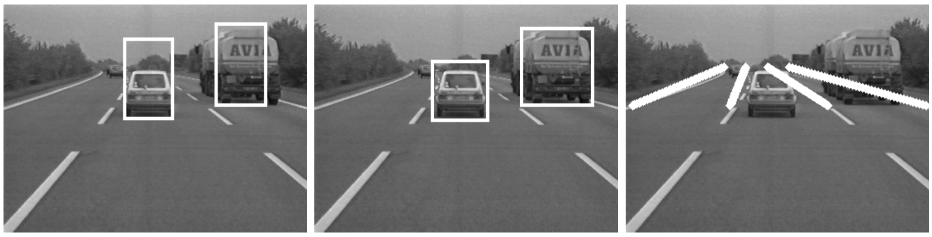


Figure 3. Object hypotheses generated by the object-related analysis (segmentation, tracking and lane information).

The dynamics is expected to determine temporal stabilized information (e.g. position) based on object information. This is actually realized using a two-dimensional dynamic field specifying the position of objects but it also can be realized as representation of free driving space or trajectories. The kind of representation can be changed according to the actual task (e.g. parking, freeway-driving, right-turn). The object-related information evaluated using the dynamics is kept in the internal memory to save object information over time for further evaluation (e.g. trajectories).

4.2. Dynamics of the internal representation

In driver assistance systems the evaluation of the incoming data from different sensor is an incident problem. Even if the data of the sensors are optimally interpreted the belief in the information generated cannot be complete, as every sensor mounted on a moving vehicle is confronted with situations which cannot be sensed correctly (e.g. darkness for a vision sensor, reflections for radar- or lidar-sensors). To overcome this problems different sensors were installed on vehicles[13] and the results were fused on different kinds of methods.[14,9] A further aspect for increasing the reliability in data gained from the real world is the temporal evaluation.[3] If e.g. an object has been detected

*logical sensors: results of algorithms working on the same sensor data at a certain position in the world at time t_0 it has to be detected in a certain region, determined by it physical properties, around this position at the time $t_0 + \Delta t$. The part of fusion of logical or physical sensor information is assumed to have been taken place at earlier stages of the architecture[10] (object-related analysis, data integration and knowledge integration). The temporal aspect of the object movement in world coordinates is regarded in the dynamics. The dynamics is supposed to select correctly detected objects and stabilize this information based on given object hypotheses. As a result of this evaluation it is expected that

- the acceptance of object-hypotheses describing non-existent objects is reduced,
- error-prone object-detections can be stabilized,
- incorrectly fused object-positions can be separated and separated ones can be fused,
- accidentally lost object-hypotheses are memorized over a certain period of time
- close objects reject each other while distant ones have no effect on each other,
- the dynamics can be actualized on different time-scales as different sensors produce output asynchronously.

The dynamics of neural fields can be designed to fulfill these properties. By choosing a 2-dimensional field with the field variables characterizing the world-position ($\mathbf{x}$-Position, $\mathbf{x} = (x, y)^\dagger$, in a bird's-eye view of the scene centered at the observing vehicle) and the field-excitation $u(\mathbf{x}, t) > 0$ presenting the reliability in the object while negative excitation is assumed to show non-existence of an object at that position. The field equation than is written as

$$\tau \dot{u}(\mathbf{x}, t) = -u(\mathbf{x}, t) + h + S(\mathbf{x}, t) + \int_\Gamma w(\mathbf{x}, \mathbf{x}')\varphi(u(\mathbf{x}', t))d\mathbf{x}' \quad . \tag{4}$$

The parts of the equation can be formulated in terms of the actual problem. The time constant dominates the reactivity of the field to new stimuli and the storage of previous information in the field. If the field reacts fast on new stimuli each object hypothesis is accepted at once and old information is erased very fast. If it reacts slowly, new information takes more time to influence the field and old information is prefered in the field excitation.

The preactivation $h < 0$ represents the basic assumption, that if no stimulus and no positive excitation is present no object can be detected.

The stimulus $S(\mathbf{x}, t)$ in eq. 4 is designed excitatory ($S(\mathbf{x}, t) > 0$) for each object hypothesis. The peak value is determined by reliability in their existence based on prior evaluations. As objects occupy a region and not only a point in the bird's-eye view each stimulus is extended to the estimated size of the object based on classification results. The advantage of the Amari-Field is that if additional information or intentions occur it can be coded additively into the stimulus. E.g. off-street positions can be coded inhibitory ($S(\mathbf{x}, t) < 0$) if objects are not relevant while not occupying driving space.

The interaction term of the dynamics determines the interaction between object-hypotheses. Hypotheses distant from each other do not interact, closer ones repell each other and hypotheses too close are fused. The borders of repellation and fusion are determined by the interaction kernel which is chosen as a Mexican Hat function

$$f_{MH}(\mathbf{x}) = c_0 \cdot e^{-\sum_{i=1}^{n}(\frac{x_i^2}{2\sigma_{0,i}^2})} - c_1 \cdot e^{-\sum_{i=1}^{n}(\frac{x_i^2}{2\sigma_{1,i}^2})}, \quad \mathbf{x} = [x_1, \cdots x_i, \cdots, x_n]^T$$

for excitatory and inhibitory elements. The size of the interaction kernel hat to be greater than the stimulus for correct evaluation. According to this restriction the function parameters are set differently in x- and y-direction (greater in y- than in x-direction). The separation of an excited region is also influenced by the interaction kernel. If one excited region becomes greater than the interaction kernel the region is splitted. The nonlinearity is chosen as a step function

$$\varphi(u(\mathbf{x}, t)) = \begin{cases} 1 & : \quad u(\mathbf{x}, t) > 0 \\ 0 & : \quad u(\mathbf{x}, t) \leq 0 \end{cases}$$

such that all excitations $u(\mathbf{x}, t) > 0$ representing an object join the interaction.

$^\dagger y$ is the longitudinal and x the lateral Position

The correct choice of the parameters of the stimulus, the interaction kernel, the time constant and the preactivation has to be performed heuristically according to the aforementioned goals, but the considerations given in section 3 limit the choice according to the desired solutions for this problem.

The desired solution for a field without any stimuli for a longer period of time is the $\emptyset$-solution because no object can be detected. If stationary stimuli are given a-solutions are needed because objects have been detected (fig 4).

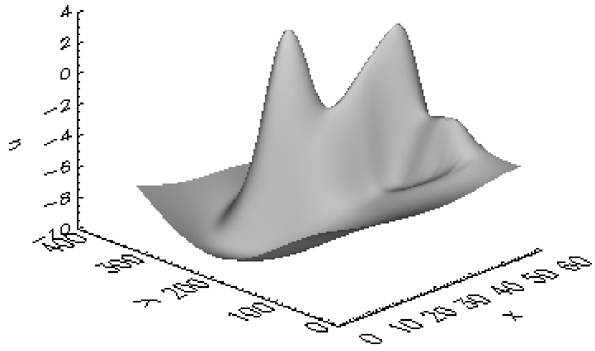


Figure 4. Two-dimensional neural field.

The evaluation of the field excitation is performed by clustering the excited regions with $u(\mathbf{x}, t) > 0$. Because of the symmetry of the interaction kernel in x- and in y-direction the position of the object is assumed to be at the center of gravity of the excited region

$$\mathbf{x_{obj}} = \int_{D_y} \int_{D_x} \mathbf{x} \cdot u_{cluster}(\mathbf{x}, t) dx dy \quad ,$$

with

$$u_{cluster}(\mathbf{x}, t) = \begin{cases} u(\mathbf{x}, t) & : \quad \mathbf{x} \in cluster \\ 0 & : \quad else \end{cases}$$

The reliability in the detected object is determined by the maximum of the excitation in the clustered region as the excitation $u(\mathbf{x}, t)$ grows with increasing detection rate (fig 5). The accepted objects and the related information are passed to the internal memory. The information from the internal memory as well as the neural field-information itself is used by the behavior planning. The relative steering angle Ψ (relative to the actual vehicle direction), the relative velocity Δv and the distance d_{obj} of the detected objects are used for the behavior planning.

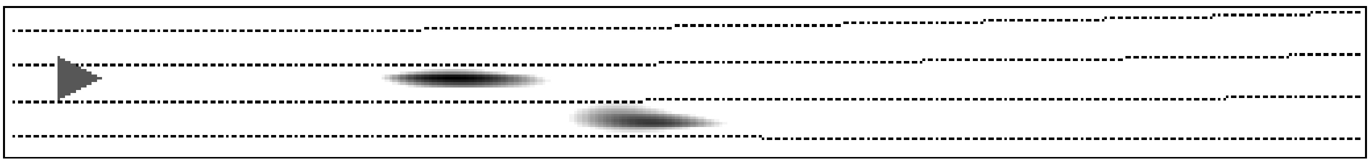
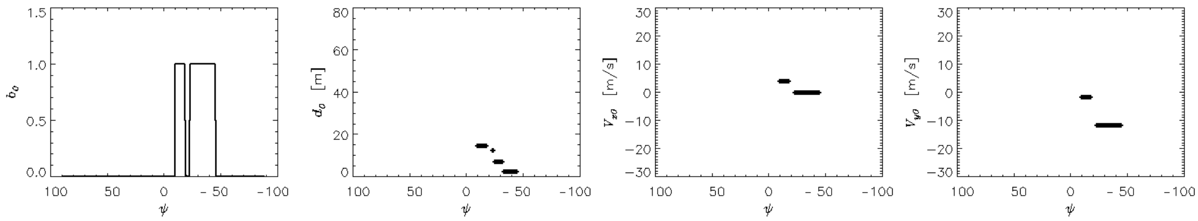


Figure 5. Bird's-eye view.

Based on the determined data and evaluating the lane-information the stimuli for the neural fields of the behavior planing are generated (fig. 6).



(a) (b) (c) (d)

Figure 6. Sensor information processing. All values are determined according to angle-coordinates Ψ of the actual view. Only objects which can be observed by the sensor are included. (a) occupancy b_o of the view concerning objects (b) distance d_o to detected objects (c),(d) relative velocity of the objects in x- and y-direction

5. BEHAVIOR PLANNING

The behavior of a vehicle can only be controlled according to the information obtained from the environment by sensors, knowledge (e.g. the state of the vehicle like steering angle and velocity) and global information (e.g. evaluated GPS-data). Those data have to be interpreted according to position, movement direction and relative velocity of relevant objects in the environment. Relevant objects are characterized by the grade of influence they have on the vehicle and by the actual task. Relevant objects can be other road users as well as traffic signs, elements of the landscape or the lane itself.

The evaluated object information and other generated data (e.g. lane estimation) are interpreted according to the information needed for behavior planning. It has to be formulated in terms of "position"-information, at which the input of the field is generated, of an stimulus-amplitude coding the grade of influence on the field activation and of the variance determining the influence over a group of neighboring field elements. For the behavior planning two one-dimensional neural fields are applied. The "position"-information of the fields are the relative steering angle Ψ (relative to the actual vehicle direction, fig. 7) and the relative velocity Δv. The grade of influence of the sensor information is related to the relevance of the object which is dependent on the Euclidean distance

$$d_{obj} = \sqrt{x_{obj}^2 + y_{obj}^2}$$

to the object, the angle Ψ_{obj} towards the object and its relative velocity Δv_{obj}. An example for the extracted information is shown in fig. 6. The view observed by the visual sensor is occupied ($b_o = 1$) by objects in a range from $\Psi \simeq -9°$ to $\Psi \simeq -45°$ (fig. 6(a)). There are four objects in different distances (fig. 6(b)), of which three parking object have the same velocity (negative velocity of the observer) differing from the velocity of the leading object.

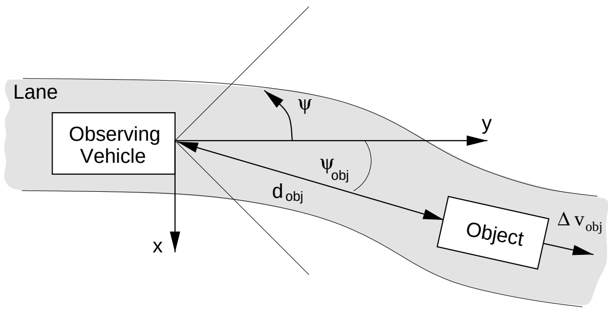


Figure 7. Observer-centered coordinate system for behavior planning. (x, y) determines the lateral and longitudinal position in Cartesian coordinates, d_{obj} and Ψ represent radial coordinates. Δv_{obj} is the relative velocity of the object.

5.1. Field dynamics

In order to determine the desired controlled variables in dependency on sensor information, knowledge, trajectory requirements and behavioral demands two one-dimensional neural fields as presented in section 3 are designed. The field positions z are set to Ψ and Δv to be able to directly apply the solutions generated by the field evaluations. The excitations $u_\Psi(\Psi)$ and $u_v(\Delta v)$ of the fields are interpreted as a continuous preference functions of which the position of the maximum is the most preferred controlled variable. For the stimulation of the fields the information needed for the control has to be formulated in those field-variables.

The field controlling the steering angle is influenced by the position and velocity informations of other road users (especially the guiding vehicle), by information describing the free driving space and by lane information. According to this information the stimulus is determined according to three stimulus-functions. The functions describe

- the danger estimate $\mathcal{O}(\Psi, t)$ for each detected object taking into account the relative speed and the distance to the object. The influence on the field must be inhibitory as the collision with objects has to be avoided.
- the street-course-factor $\mathcal{L}(\Psi, t)$, which is determined for one reference distance to ensure a smooth trajectory within the actual lane. The stimulus is designed excitatory with the center of the lane showing the greatest attraction to the vehicle.
- the direction towards $\Psi\mathcal{D}(\Psi, t)$ of the leader. The vehicle is supposed to follow the leader, so the direction towards the leader has to be an excitatory stimulus in the field.

The stimuli-functions are distributed over a certain range of angles by a convolution with a Mexican Hat function. The convolution is performed to regard the variances and the distribution of information over neighbored angle values. For each stimulus the convolution

$$S_i(\Psi, t) = \int_{-\gamma}^{\gamma} f_{MH,i}(\Psi - \Psi') \cdot i(\Psi', t) d\Psi' + \eta_i$$

is performed, where i can be replaced by $\mathcal{O}$, $\mathcal{L}$ or $\Psi\mathcal{D}$ for the different stimuli-functions. The convolution is performed over the whole range of $\psi' \in [-\gamma, \gamma]$. The function $f_{MH,i}$ is parameterized with different values for the three functions $f_{MH,i}(\Psi - \Psi')$. The threshold

$$\eta_{0,i} = \begin{cases} \eta_{\mathcal{O}} & , \quad i = \mathcal{O} \\ 0 & , \quad i = \mathcal{L}, \Psi\mathcal{D} \end{cases}$$

is introduced, as a high inhibition value has to be put on the field if a dangerous situation concerning other objects occurs, which is supposed to out-range the lane- and the leader-stimulus very fast. The magnitudes of the different stimuli-functions must be adapted to the desired effect on the neural field. In case of cruise control a smooth trajectory following the leader is demanded until the influence of other objects requires different actions (collision avoidance). The stimulus of the field for the steering angle at time t is then determined by

$$S_\Psi(\Psi, t) = -S_{\mathcal{O}}(\Psi, t) + S_{\mathcal{L}}(\Psi, t) + S_{\psi\mathcal{D}}(\Psi, t) \quad . \tag{5}$$

The field controlling the velocity is influenced by the actual velocity, the velocity to be reached according to actual traffic rules and the relative velocity of the leader. There a two stimuli-functions which are imposed on the neural field:

- the stimulus $S_{\mathcal{R}}(\Delta v)$ based on speed limits or favored speeds is realized as a Mexican Hat function centered at the difference between the magnitude of the actual and of the intended velocity. The magnitude of the stimulus is chosen such that it is dominant if the distance to the leader is greater than security distance, otherwise the leader's velocity should dominate the change in velocity.
- the stimulus $S_{v\mathcal{D}}(\Delta v)$ invoked by the leader is a Mexican Hat function centered at the magnitude of the relative velocity of the leader. The magnitude of the stimulus is proportional to the distance and time derivative to the leader (e.g. if the leader has a lower velocity than the ruled velocity, the leader will approach the observing vehicle, so the observer-velocity has to be reduced proportional to the change of distance to avoid a collision).

Both stimuli are supposed to have excitatory influence on the field excitation because each velocity is supposed to attract the field. The change in velocity, Δv, is determined as a result of the field dynamics, where the position of the maximum represents the advised change in velocity. The stimulus of the velocity field is build additively

$$S_v(\Delta v, t) = S_{\mathcal{R}}(\Delta v, t) + S_{v\mathcal{D}}(\Delta v, t) \quad . \tag{6}$$

The field equation for both neural fields are given by the formulation of the Amari-equation (eq. 1)

$$\tau_\Psi \dot{u}_\Psi(\Psi,t) \quad = -u_\Psi(\Psi,t) + h_\Psi + S_\Psi(\Psi,t) + \int_{\Gamma_\Psi} w_\Psi(\Psi,\Psi')\varphi_\Psi(u(\Psi',t))d\Psi'$$

and

$$\tau_v \dot{u}_v(\Delta v,t) \quad = -u_v(\Delta v,t) + h_v + S_v(\Delta v,t) + \int_{\Gamma_v} w_v(\Delta v,\Delta v')\varphi_v(u(\Delta v',t))d\Delta v'.$$

The time constants τ_Ψ and τ_v are chosen according to the time scale on which the field is supposed to react on the stimulus. The preactivations h_Ψ and h_v were set to the value of -1 for both fields. The stimuli are determined according to eqs. 5 and 6. Both interaction kernels $w_\Psi(\Psi,\Psi')$ and $w_v(\Delta v,\Delta v')$ are realized as Mexican Hat functions parameterized according to eq. 2. As nonlinearities $\varphi_\Psi(\Psi,t)$ and $\varphi_v(v,t)$ tanh-functions shifted to the range $[0,1]$ are used. The convolution is performed over the set Γ_Ψ and Γ_v of the field-sites respectively.

The evaluation of the field-excitation is performed by the determining the position of the maximum

$$\mathcal{N}_\Psi(t) = \arg\max_\Psi u_\Psi(\Psi,t)$$

for the change in steering angle and by

$$\mathcal{N}_v(t) = \arg\max_v u_v(\Delta v,t)$$

for the change in velocity. For security considerations thresholds $\mathcal{N}_{\Psi,max}$ and $\mathcal{N}_{v,max}$ for Ψ and Δv are applied regarding the maximal allowed range of change. The applied change in steering angle is determined by the minimum operation

$$\Psi_{control} = sign(\mathcal{N}_\ominus)\cdot\alpha_{\mathcal{N}_\Psi}\min\left(|\mathcal{N}_\Psi|,\mathcal{N}_{\Psi,max}\right)$$

and the change in velocity by

$$\Psi_{control} = sign(\mathcal{N}_v)\cdot\alpha_{\mathcal{N}_v}\min\left(|\mathcal{N}_v|,\mathcal{N}_{v,max}\right) \quad .$$

The variables $\alpha_{\mathcal{N}_\Psi}$ and $\alpha_{\mathcal{N}_v}$ are velocity dependent factors to take into account the dynamics of the vehicle.

To examine the behavior of the designed cruise control different traffic scenes were generated by the simulation program. The parameters of the field-equations and the stimuli are determined by evaluating the reaction of the system for a variety of scenes. The results for one simulated scene are presented in the next section to give an illustration of the field dynamics.

A result for the field excitations of the behavior planning module at time t_0 are shown in fig. 8. According to those data the stimuli of both fields were determined and are shown as dashed lines in fig. 8 (for presentation purposes the stimuli where shifted upwards from the zero-line). For the presented situation the field excitations have a single maximum at $\Psi \simeq 1^\circ$ and at $\Delta v \simeq -9m/s$. The presence of single peak solutions proofs the reliability of the controlled variable for Ψ and Δv.

The field-excitation for the steering angle show negative values at the positions of objects to be avoided (e.g. parking vehicles in view) and positive values at angle positions to be favored (e.g. leading object and lane). The maximum of the field-excitation is shifted to the left as long as the parking vehicles can be detected, so the vehicle does not drive in the center of the lane but a little bit shifted to the left, to keep a security distance towards the parking vehicles.

The velocity is a smooth function of time. The vehicle is not decelerated or accelerated abruptly because no dangerous situation occured. While the leader gets closer, the velocity of the observing vehicle is reduced such that the leader is within security distance finally. The change in velocity is reduced smoothly until the observing vehicle reaches the speed of the leading vehicle. The field-excitation amplifies the decision imposed by the stimulus.

6. CONCLUSIONS

This paper shows the applicability of neural fields to the problem of scene interpretation and behavior planning in driver assistance systems. The scene interpretation module includes a two-dimensional neural field for organizing a representation to analyze the constellation of the relevant objects around the vehicle.

The special behavior of cruise control was selected and the stimuli of two one-dimensional neural fields controlling steering angle and velocity were designed to fulfill this task. The obtained values for the change in steering angle and in velocity resulted in a comfortable trajectory and driving speed.

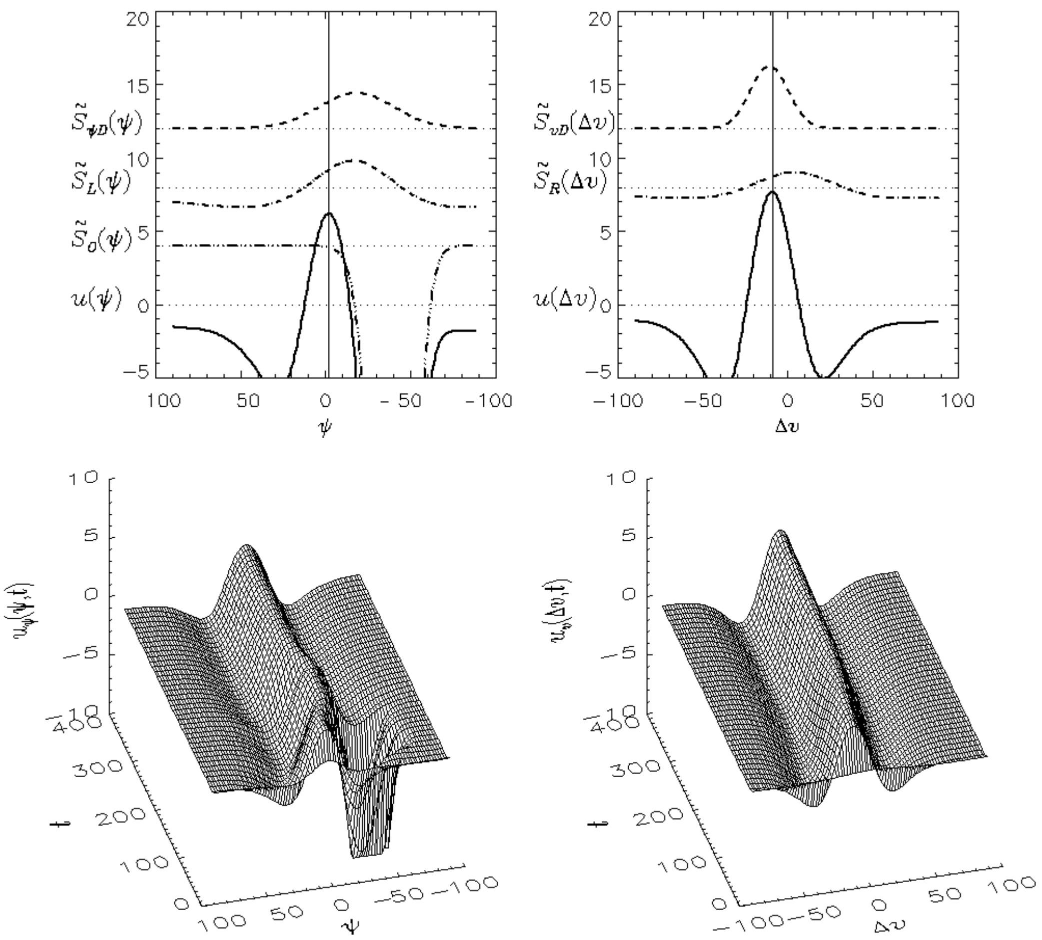


Figure 8. Excitation of a neural fields. Additionally the stimulus according to objects, lane, leader and intended velocity are presented (shifted to a virtual zero). Left: neural field controlling the steering angle. Right: neural field controlling the velocity.

REFERENCES

1. M. Rossi, M. Aste, R. Cattoni, and B. Caprile, "The IRST Driver's Assistance System," Technical Report 9611-01, Instituto per la Ricerca Scientificia e Technologica, Povo, Trento, Italy, 1996.
2. S. Goerzig and U. Franke, "ANTS - Intelligent Vision in Urban Traffic," in *IV'98, IEEE International Conference on Intelligent Vehicles 1998*, pp. 545–549, IEEE, (Stuttgart, Germany), 1998.
3. E. Dickmanns *et al.*, "Vehicles capable of dynamic vision," in *15th International Joint Conference on Artificial Intelligence (IJCAI)*, pp. 1–16, (Nagoya, Japan), 1997.
4. M. Bertozzi and A. Broggi, "GOLD: a Parallel Real-Time Stereo Vision System for Generic Obstacle and Lane Detection," in *IEEE Transactions on Image Processing*, IEEE, ed., vol. 7(1), pp. 62–81, 1998.
5. S.-I. Amari, "Field Theory of Self-Organizing Neural Nets," *IEEE Transactions on Systems, Man, and Cybernetics* **13**, 1983.
6. J. Taylor, "Neural 'bubble' dynamics in two dimensions: foundations," *Biological Cybernetics* , 1999.
7. S. Amari, "Dynamics of pattern formation in lateral inhibition type neural fields," in *Biological Cybernetics*, vol. 27, pp. 77–87, Springer Verlag, 1977.

8. U. Handmann, I. Leefken, C. Tzomakas, and W. von Seelen, "A Flexible Architecture for Driver Assistance," in *SPIE's International Symposium on Intelligent Systems and Advanced Manufacturing 1999 (Mobile Robots and Autonoumous Systems), Proceedings of SPIE Vol. 3838*, pp. 2 – 11, SPIE, (Boston), 1999.
9. U. Handmann, G. Lorenz, T. Schnitger, and W. von Seelen, "Fusion of Different Sensors and Algorithms for Segmentation," in *IV'98, IEEE International Conference on Intelligent Vehicles 1998*, pp. 499 – 504, IEEE, (Stuttgart, Germany), 1998.
10. U. Handmann, T. Kalinke, C. Tzomakas, M. Werner, and W. von Seelen, "An Image Processing System for Driver Assistance," *Image and Vision Computing (Elsevier)* **18**(5), pp. 367 – 376, 2000.
11. U. Handmann, I. Leefken, C. Tzomakas, and W. von Seelen, "A Flexible Architecture for Intelligent Cruise Control," in *ITSC'99, IEEE Conference on Intelligent Transportation Systems 1999*, pp. 959 – 963, IEEE, (Tokyo, Japan), 1999.
12. M. Arbib and S. Amari, *Dynamic Interactions in Neural Networks: Models and Data*, Springer-Verlag, 1989.
13. B. Ulmer, "VITA II - Active Collision Avoidance in Real Traffic," in *Proceedings of the Intelligent Vehicles '94 Symposium, Paris, France*, pp. 1–12, 1994.
14. B. V. Dasarathy, *Decision Fusion*, IEEE Computer Society Press, Los Alamitos, 1994.