Detection of Moving and Stationary Objects at High Velocities using Cost-Efficient Sensors, Curve-Fitting and Neural Networks

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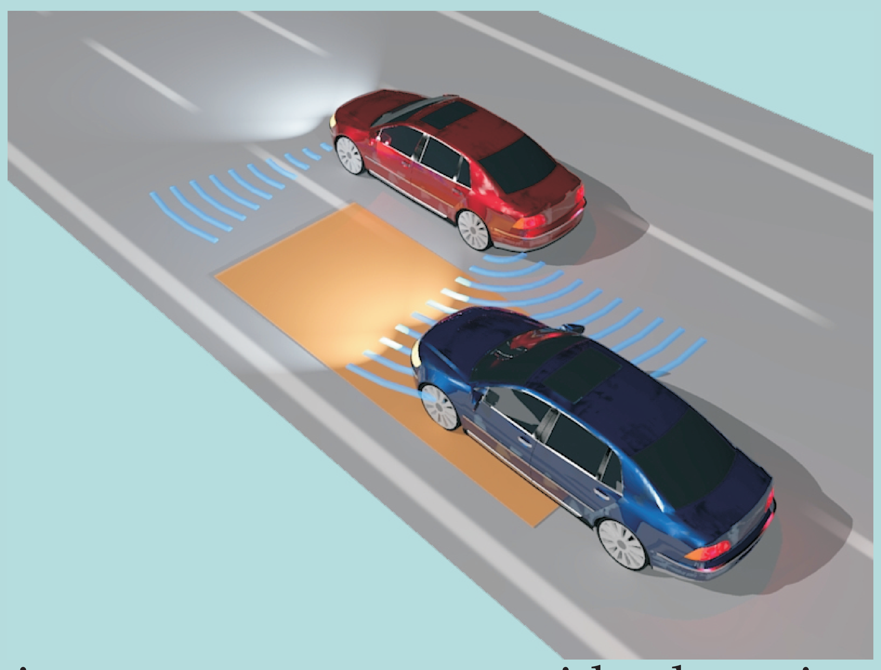
Abstract

The work at hand investigates the usage of cost-efficient, widely used ultrasonic sensors for blind spot warning at high velocities. After discussing the requirements and setup of such a system a model-based approach for the detection of moving and stationary objects is outlined. The sensor-signal is compared with a precalculated curve data base and the correlation-coefficients are feeded into a neural network. To revise its performance the concept at hand is qualitatively and quantitatively evaluated in real road traffic situations under different driving conditions.

System Setup

PROBLEM STATEMENT:

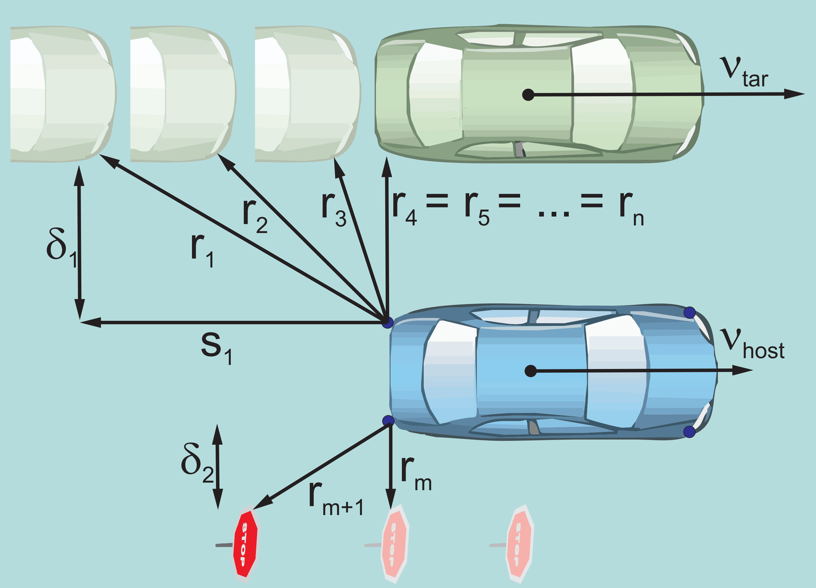


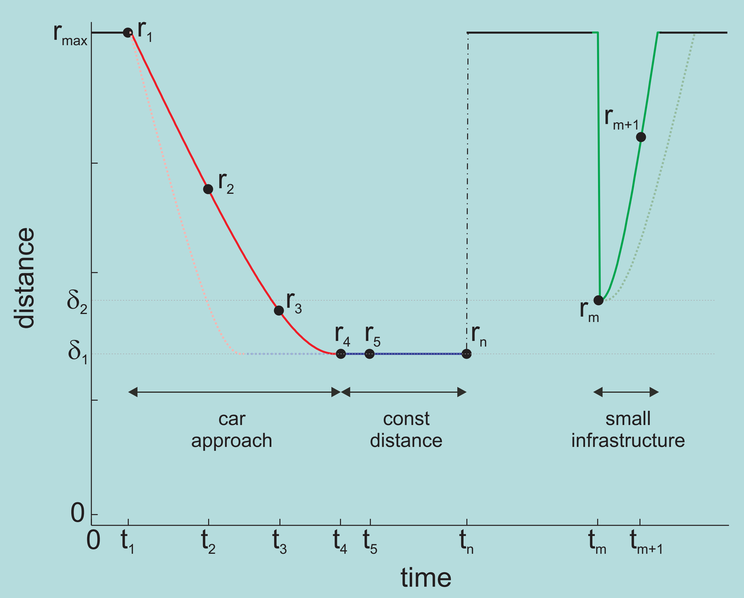
The goal of a blind spot surveillance system is to assist the driver when changing lanes and avoid possibly dangerous situations. The blind spot zone ranges from $3\mathrm{m}$ behind the car to the side mirrors and $3\mathrm{m}$ laterally. A warning signal shall be emitted when a car occurs within this zone during a lane change.

APPROACH: The incoming ultrasonic measurements provide the minimal distance of the sensor to the object which reflected the ultrasonic beam in meters. Analysis of simulations as well as real road situations show that most overtaking maneuvers can be modelled by a parallel passing of two objects with constant orthogonal distance. This results ideally in a parabolic measurement signal.

Curve Fitting

PATTERN SIGNAL DEVELOPMENT:





The functions used for modelling overtaking maneuvers have the form

$$f_i(t) = \sqrt{a_{i2}t^2 + a_{i1}t + a_{i0}} \text{ with}$$

$\delta_i \in \{0.5, 1, 1.5, \dots, 4\}$ orthogonal distance in m,
$\nu_i \in \{1, 3, 5, \dots, 15\}$ velocity relative to the host speed in $\mathrm{m/s}$.

$$f_i(t)^2 = \delta_i^2 + s_i(t)^2 \text{ with } s_i(t) = s_{max} - \nu_i t$$

$$\text{and } s_{max} = \sqrt{r_{max}^2 - \delta_i^2}.$$

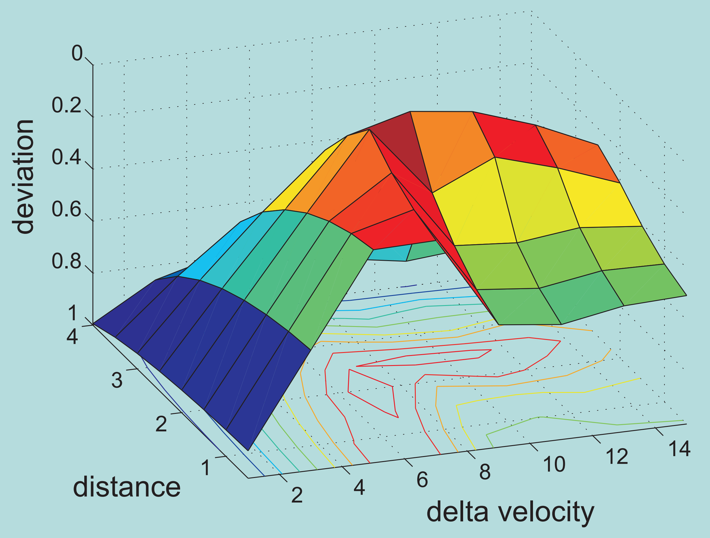
$$\Rightarrow f_i(t)^2 = \underbrace{\nu_i^2}_{:=a_{i2}} t^2 \underbrace{-2\nu_i\sqrt{r_{max}^2 - \delta_i^2}}_{:=a_{i1}}\, t + \underbrace{r_{max}^2}_{:=a_{i0}},$$

DEVIATION FUNCTION: $W_m := \{x_1, \dots, x_n\}$, $y_{ij} := f_i(t_j)$

$$F(W_m, f_i) :=$$

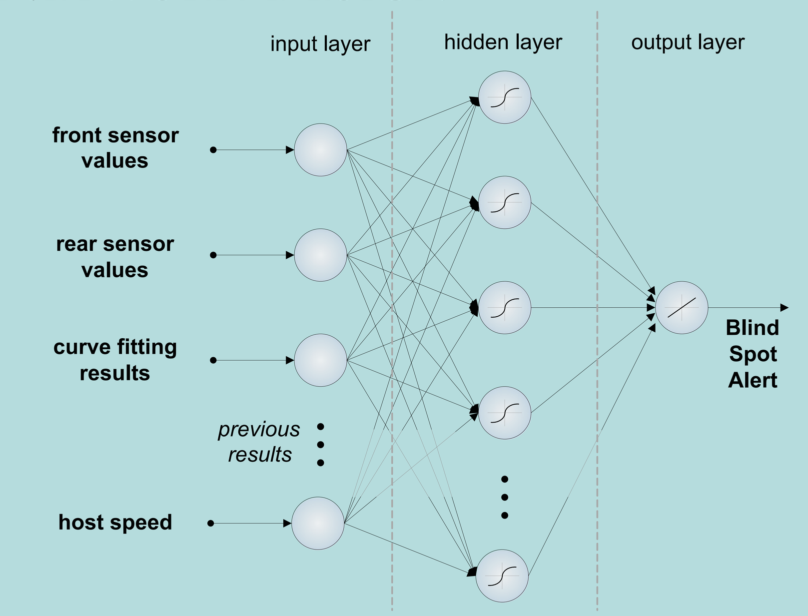
$$\min_{f_i,k}\Big\{ \sum_{\substack{j=1\\ j\neq j_{max}}}^{n} |x_j - y_{i(j+k)}| \Big\}$$

$$\text{with } j_{max} = \max_j\{|x_j - y_{i(j+k)}|\}$$



Neural Networks

NETWORK DESIGN:



Since the curve data base is calculated over a lattice of orthogonal distance and relative velocity, it is impossible to detect a unique fitting function in most cases. There are several functions with similar deviation values. An artificial neural network is able to tackle this problem and refine the decision process.

This input values are the sample mean and covariance of all sensors in the current moving window W_m, the results of the curve-fitting-process represented by a state variable indicating whether an approaching car, a stationary object, constant distance or none of those cases has been detected and the sum of the detected states covering the last second of measurements. Additionally, the deviation function $F(W_m, f)$ of the best fitting function f for every state and the host vehicle's velocity is entered.

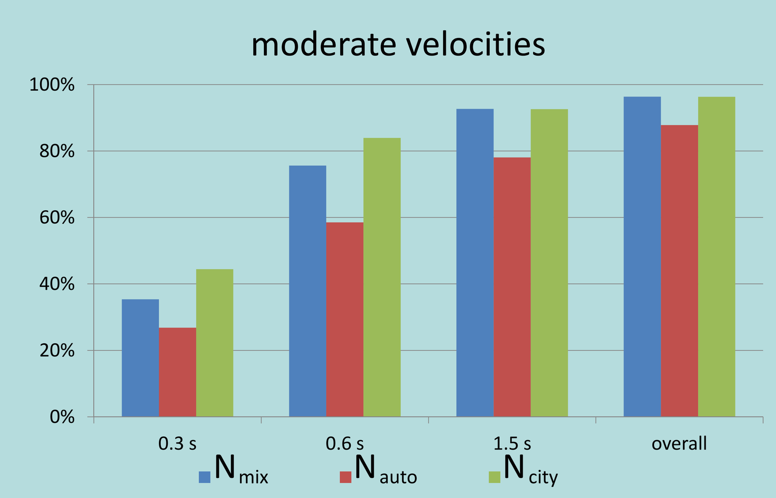
TRAINING: The work at hand demonstrates three neural networks N_{auto}, N_{city} and N_{mix}. The training set of N_{auto} contains three motorway files with $45\mathrm{km}$ driven distances and 88 overtaking maneuvers, N_{city} was trained using two inner city files with $10\mathrm{km}$ driven distance and 46 overtaking maneuvers and the underlying training data of N_{mix} is a combination of these motorway and inner city test drives in a ratio of 3:2 with $55\mathrm{km}$ driven distance and 134 overtaking maneuvers.

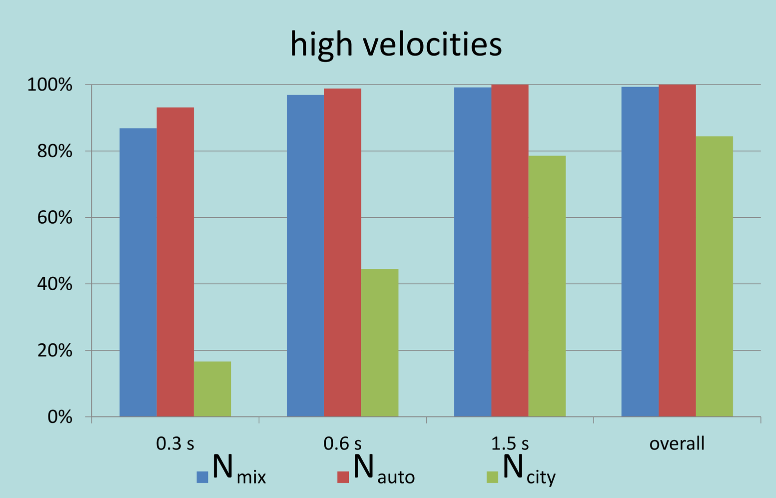
Evaluation

STATISTICS: To revise the functionality and perfomance of the proposed procedure, extensive testing has been conducted. The host vehicle was equipped with one laser sensor on each side and four color cameras mounted on top of the car to generate a 360° view of the environment. In order to ensure meaningful results, differing types of target vehicles like cars, motorbikes or trucks and different road environments like inner city, interurban or motorway drives had to be considered. After more than $2000\mathrm{km}$ of test drives, the data base contains over 3000 test cases for qualitative and quantitative evaluation. In the table below the overall-performance is outlined.

	0.3 s	0.6 s	1.5 s	overall	FA	high-speed FA
N_{mix}	75.0%	90.8 %	96.2 %	97.1 %	7.3 %	4.8 %
N_{auto}	81.5%	91.6 %	95.1 %	97.1 %	16.1 %	7.9 %
N_{city}	23.5%	51.8 %	79.4 %	84.6 %	21.7 %	23.7 %

The results demonstrated below show that the networks N_{auto} and N_{city} achieve promising detection rates for the particular driving situations they have been trained for. As expected N_{city} performs best in terms of moderate velocities where a slightly elevated reaction time is acceptable achieving an overall detection rate of 96.3% and even 84% within 0.6s. Analogously, N_{auto} provides satisfying detection rates in terms of high velocities detecting all vehicles and even 93.1% within 0.3s. The one-size-fits-all network N_{mix} provides low false-alarm-rates in the overall and high-speed setting in exchange for a slightly elevated reaction time but still achieving overall detection rates of at least 96.3% in every setting.





PROSPECT: As a start the results of the neural network approach at hand show promise. Since every network has its strengths in particular situations, the training of different networks for several situations is prefered for a deeper analysis. Another aspect demanding further investigations is a neural network trained for rain weather conditions including wet roads and splash water. In this case, the ultrasonic sensor signal contains a lot of noise, so it might be necessary to consider alternative reference functions.