

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

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Abstract—In recent years, driver-assistance systems have emerged as one major possibility to increase comfort and – even more important – safety in road traffic. Still, cost is one major hindrance to the widespread use of safety systems such as lane change or blind spot warning. To facilitate the widespread adoption of such assistance systems, thus increasing safety for all traffic participants, the use of cost-efficient components is of crucial importance.

This paper 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.

I. INTRODUCTION

During the last decade, autonomous driving has made a huge jump from the first DARPA challenge [1] over the last Urban Challenge [2], [3], [4] to the latest experiments of Google in the field of autonomous driving. Although legal considerations and costs might be an insurmountable obstacle for a long time, driver-assistance systems have emerged as one major possibility to increase comfort and safety in road traffic [5].

Besides mainly introspective systems such as ABS and ESP recent developments [6] build more and more on exteroceptive sensors to detect and react on potentially dangerous situations. To facilitate the widespread adoption of such assistance systems the use of cost-efficient components is of crucial importance. Ultrasonic sensors fulfill these requirements on cost-efficiency. Consequently, they are widely used in the automotive industry for periphery surveillance in context of low velocities [7], [8], [9]. A prominent example is the meanwhile ubiquitous parking assistant, giving feedback on the distance to possible obstacles while the driver is backing into a parking lot. However, the sensitivity of ultrasonic sensors to external disturbances such as gusts of wind or rain and their restricted range [10], [11] was for a long time prohibiting in context of high-speed applications, such as the detection of cars in the blind spot of the driver. Another hindrance is the comparably low amount of information

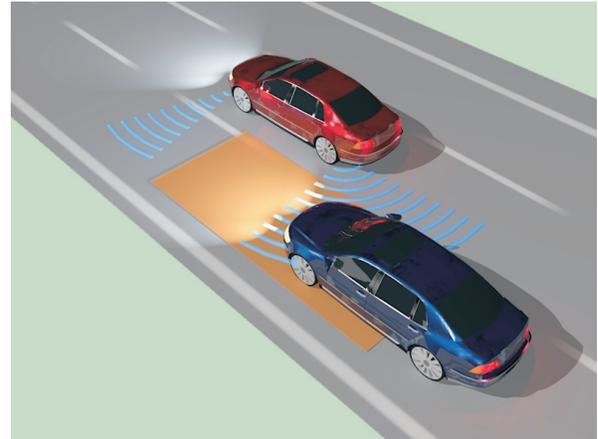


Fig. 1. Approaching car in the host vehicle's blind spot

contained in the signal. In contrast to more expensive radar, lidar or camera systems [12], [13] that offer an acceptable angular resolution, us-sensors often have a wide aperture. That makes it difficult to distinguish the source or location of an echo.

The work at hand provides an insight into the development of a lane-change-assistent system using cost-efficient ultrasonic-sensors for the detection of objects in the driver's blind spot zone at absolute velocities of up to 160 km/h. A fuzzy-markov based approach using an inverse-geometric model has been proposed in [14] achieving promising detection rates. One hindrance is that this concept delivers no information about the type and velocity of the object in the blind spot zone. Another problem is the high number of underlying parameters that need to be tuned individually.

To tackle these issues, the work at hand investigates a model-based approach incorporating artificial neural networks. These networks [15], [16] are applied to diverse tasks like image analysis for traffic sign recognition in terms of driver-assistance or car identification. The outlined approach compares the ultrasonic signal with a precalculated curve data base for different situations in the blind spot zone like approaching cars, infrastructure or stationary objects. The correlation-coefficients are feeded into an artificial neural network and the trained network is used for the decision process.

This paper is organized as follows. In Section II the system-requirements and setup are discussed. Section III focuses on the design of the algorithm incorporating curve-fitting and neural networks. In Section IV the results are statistically

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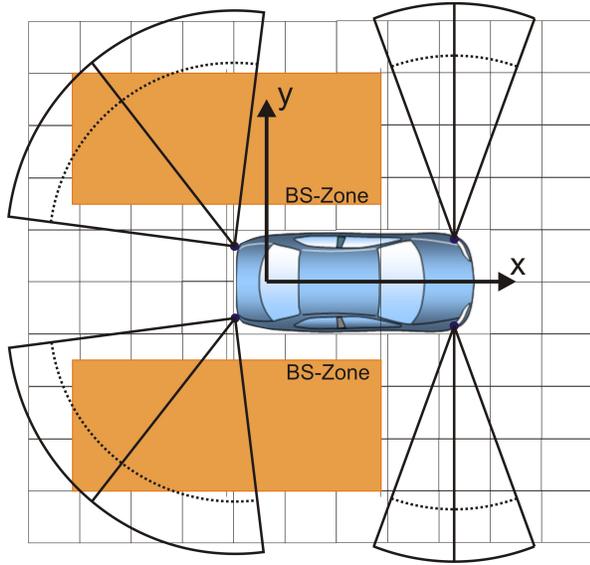


Fig. 2. Outline of the host car setup with ultrasonic sensor cones and orange blind spot zone; the grid is composed by 1 m to 1 m tiles

evaluated by comparing them to the requirements discussed in Section II. A little prospect on possible improvements concludes this paper.

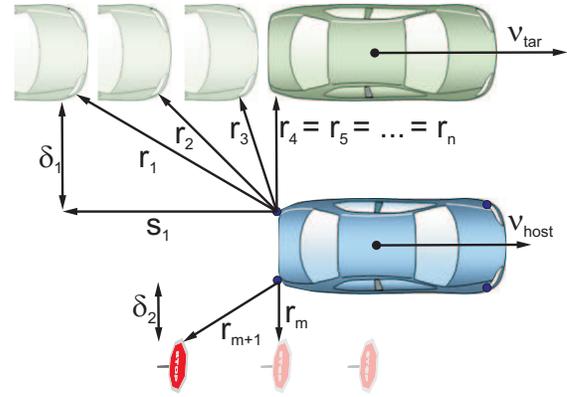
II. PROBLEM FORMULATION

A. Preliminaries

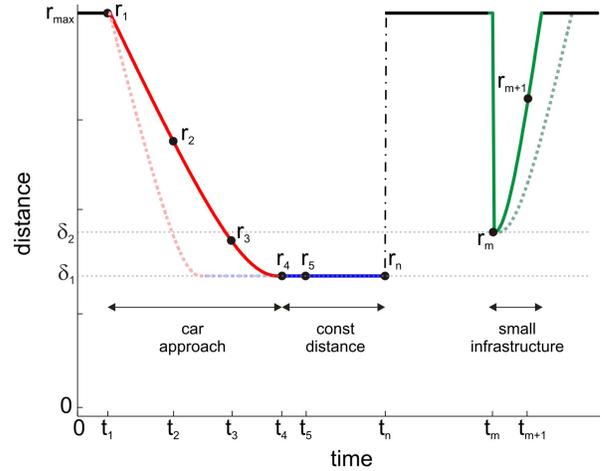
The goal of a blind spot surveillance system is to assist the driver when changing lanes and avoid possibly dangerous situations. The blind spot zone ranges from 3 m behind the car to the side mirrors and 3 m laterally. A warning signal shall be emitted when a car occurs within this zone during a lane change. To ensure applicability, some preconditions are necessary. For an optimal performance, a maximal reaction time of 300 ms is desired and the overall detection time should not exceed 1500 ms. A low false-alarm-rate is also required since too many missed or unnecessary warnings corrupt the driver's faith in the system's reliability. The operating range must be designed to detect blind spot alerts to a speed difference between the host and traffic from 0 to 30 km/h.

B. System Setup

The host vehicle is equipped with 12 ultrasonic sensors equally positioned at its front and its back side. To detect overtaking vehicles, the approach at hand evaluates the measurements of two sensors on each side of the host (dark black cones in Figure 2), namely the front and rear outer sensor. All other sensors are not used for blind spot detection. The aperture of the two rear sensors is approximately 75° , while the aperture of the front sensors is set to 45° . This enables sharp measurements with the front sensor in order to detect incoming traffic from the front or outgoing traffic from the back. In case of traffic residing within the blind spot zone, the driver is notified by illuminating a red light in its side mirror.



(a) Overtaking maneuver and pass of a traffic sign



(b) Corresponding sensor signals

Fig. 3. Correlation of driving situations and sensor signals

III. REALIZATION

A. Curve-Fitting

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.

Figure 3 illustrates the signal development for a car approaching from behind and the host passing a traffic sign. At timestamp t_1 the target enters the rear left sensor's range with measured distance r_1 . The approach happens during t_2, t_3 with sensor measurements r_2, r_3 . Then the target vehicle drives parallel to the host and the input signal fades to constant measured distances r_4, \dots, r_n . When the target leaves the rear sensor's range, the signal rebounds to its maximum. Analogously, the measurements r_m and r_{m+1} describe a traffic sign passed by the host with an almost vertical line at timestamp t_m fading to an ascending parabolic function at t_{m+1} . Obviously, driving beside infrastructure like walls or side rails can be modelled by horizontal signal lines.

The dependance of the functions on the orthogonal distance

and the velocity is illustrated by the dotted lines in Figure 3(b). The orthogonal distance δ determines the maximal signal amplitude in vertical direction.

The velocity affects the signal structure as follows. A higher relative velocity $v_{rel} = v_{tar} - v_{host}$ causes a higher instantaneous rate of change in the signal curve describing the minimal distance to the target vehicle which is denoted by the dotted red line in Figure 3(b). Analogously, a lower host speed v_{host} results in a slower rise of the distance to the traffic sign denoted by the dotted green line in Figure 3(b). The functions used for modelling overtaking maneuvers have the form

$$f_i(t) = \sqrt{a_{i2}t^2 + a_{i1}t + a_{i0}} \quad (1)$$

with coefficients a_{ij} depending on the orthogonal distance δ and the velocity v_{rel} relative to the host speed to compare the signal with. Let

$$\delta_i \in \{0.5, 1, 1.5, \dots, 4\} \text{ in m}, \quad (2)$$

$$v_i \in \{1, 3, 5, \dots, 15\} \text{ in m/s} \quad (3)$$

and r_{max} be the maximal range of the sensor, the coefficients are calculated as follows: the sensor signal, i.e. the minimal distance of the sensor to the object, is modelled by the function $f_i(t)$, which shall be expressed in dependency on δ_i and v_i . As a start the pythagorean theorem is used to express

$$f_i(t)^2 = \delta_i^2 + s_i(t)^2 \quad (4)$$

in dependency on the orthogonal distance δ_i , the distance driven by the target vehicle

$$s_i(t) = s_{max} - v_i t \quad (5)$$

and the maximal parallel sensing distance

$$s_{max} = \sqrt{r_{max}^2 - \delta_i^2}. \quad (6)$$

By application of the equations 5 and 6, equation 4 is transformed to

$$f_i(t)^2 = v_i^2 t^2 - 2v_i \sqrt{r_{max}^2 - \delta_i^2} t + r_{max}^2, \quad (7)$$

so the coefficients in equation 1 are

$$a_{i0} = r_{max}^2, \quad a_{i1} = -2v_i \sqrt{r_{max}^2 - \delta_i^2}, \quad (8)$$

$$a_{i2} = v_i^2. \quad (9)$$

Analogously the parabolic signals caused by stationary objects in the blind spot zone are modelled by functions $f_i(t)$. In this case the host vehicle's velocity v_{host} and the relative speed $v_{rel} = v_{host} - 0$ coincide. The descending part of the function can be neglected (see Figure 3). Infrastructure like walls or side rails is modelled by horizontal signal lines. Hence, the function data base contains 64 functions depending on δ_i and the relative velocity v_i for the detection of approaching cars, 8 functions depending on δ_i and the host speed v_{host} for the detection of small stationary objects and horizontal lines simulating walls or side rails depending on the sample mean of the measurements.

A moving window containing n sequenced measurements

of size $n = 8$ for short term and $n = 32$ for long term analysis is considered. Let $W_m = \{x_1, \dots, x_n\}$ be the set of the incoming data. For better results $2n$ function values $W_{f_i} = \{y_{i1}, \dots, y_{i(2n)}\}$ are calculated and all subsets $\{y_{i(1+k)}, \dots, y_{i(n+k)}\}$ for $k = 0, 1, \dots, n$ containing n sequenced elements of W_{f_i} are compared with W_m . For some curves additional modifications like considering only the relevant function values (i.e. ignoring too many subsequent constant values) and shifting them to the center of the window in order to improve the detection are made. The first algorithmic step is the choice of an adequate f_i satisfying

$$\min_{f_i, k} \left\{ \sum_{\substack{j=1 \\ j \neq j_{max}}}^n |x_j - y_{i(j+k)}| \right\} =: F(W_m, f_i) \quad (10)$$

with

$$j_{max} = \max_j \{|x_j - y_{i(j+k)}|\}. \quad (11)$$

From the coefficients of the chosen function f the target vehicle's orthogonal distance to the host and relative speed can be recalculated as follows

$$v = \sqrt{a_2}, \quad \delta = \sqrt{r_{max}^2 - \frac{a_1^2}{4a_2}}. \quad (12)$$

Along with the characteristic values sample mean and covariance in every sensor's moving window W_m the calculated distance δ and relative velocity v form the input data of the neural network.

B. Neural Networks

1) *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. As illustrated in Figure 4, there are several functions with similar deviation values. An artificial neural network is able to tackle this problem and refine the decision process.

In this paper a feedforward neural network, which means that there are no cycles within, containing twenty neurons within the hidden layer is used. The training was realized by supervised learning using the recorded data from different test drives as input values for the Levenberg-Marquardt-Algorithm.

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. The approach at hand is illustrated in Figure 5.

The neural network's binary output value is 1 if a possibly dangerous state has been detected, 0 otherwise. A warning is emitted, if two of the last three output values are nonzero.

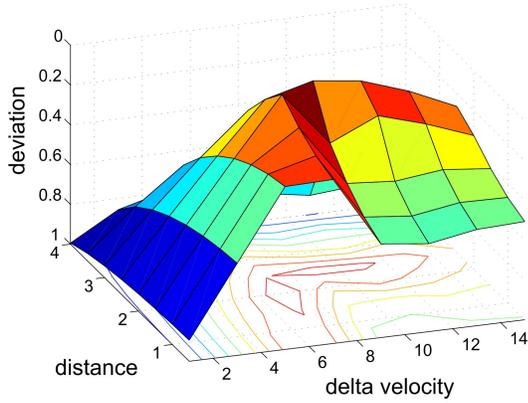


Fig. 4. Deviation function over the distance-velocity-lattice

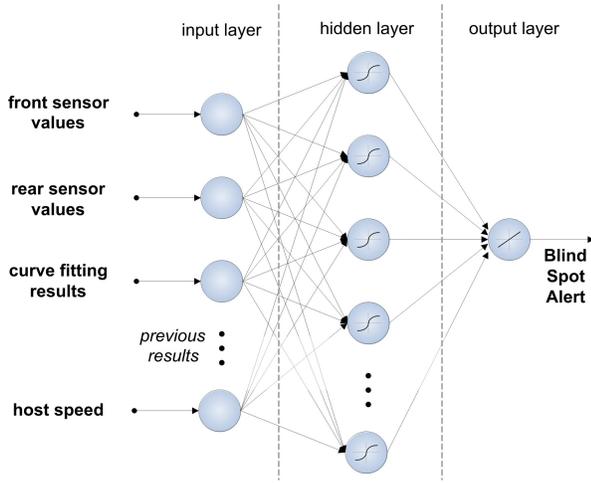


Fig. 5. Neural network for the detection of overtaking cars

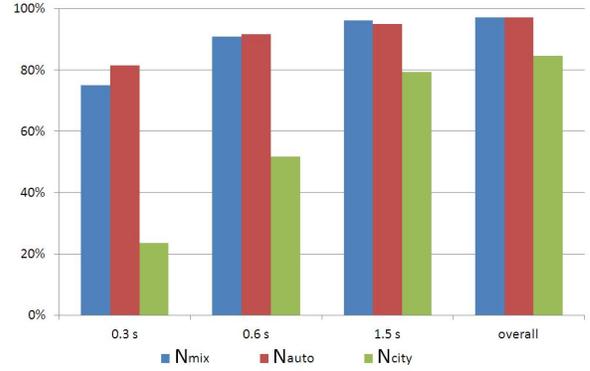
2) *Training*: There are several ways to realize this neural network approach. One possibility is to train different networks for each environment namely inner city, interurban and motorway traffic. Another idea is to design some kind of one-size-fits-all network, whose training set contains a mix of test drives in different environments.

The work at hand illustrates both possibilities demonstrating three neural networks N_{auto} , N_{city} and N_{mix} . The training set of N_{auto} contains three motorway files with 45 km driven distances and 88 overtaking maneuvers, N_{city} was trained using two inner city files with 10 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 km driven distance and 134 overtaking maneuvers. In this first attempt interurban drives have been left out of the training files since the chosen networks are expected to cover that cases at a satisfying level.

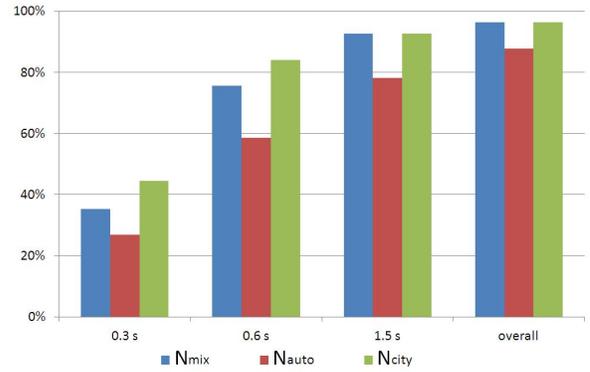
IV. RESULTS

A. Statistical Evaluation

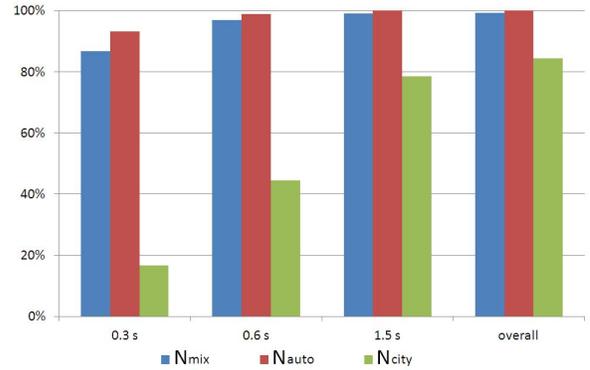
To revise the functionality and performance of the proposed procedure, extensive testing has been conducted. The host



(a) Detection rates without host speed limits



(b) Detection rates within 25 km/h to 50 km/h (moderate speed)



(c) Detection rates within high-speed-interval (over 70 km/h)

Fig. 6. Statistical evaluation of detection rates for different host speed intervals

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 km of test drives, the data base contains over 3000 test cases for qualitative and quantitative evaluation.

The three networks N_{auto} , N_{city} and N_{mix} have been applied to a collection of test files containing approximately 356 km driven on motorways and additionally about 20 km and 32 km driven in city respectively interurban traffic.

According to the requirements stated in Section II-A the

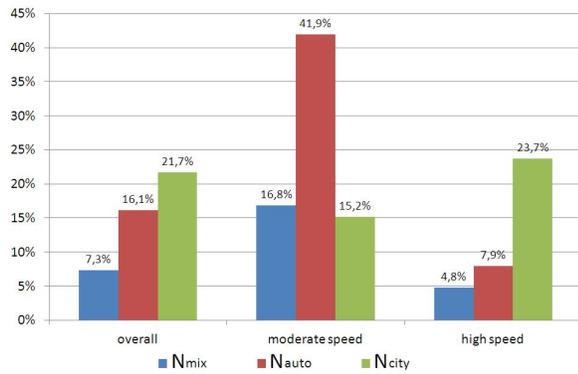


Fig. 7. False-alarm-rate for all networks and different host speed intervals

desired maximal reaction time shall not exceed 300 ms. Hence detection intervals of 0.3 s, 0.6 s, 1.5 s and the overall detection rate without any time limit are statistically evaluated. The performance of the networks is compared in three settings with different host speed intervals to illustrate their particular strengths. Figure 6 illustrates the detection rates for the different speed-intervals. The first setting, illustrated in Figure 6(a), has no limitations concerning the host vehicle's speed to illustrate the overall performance of all networks. Figure 6(b) shows the results in the second interval (moderate-speed-interval) ranging from 25 km/h to 50 km/h to evaluate the inner city efficiency. Finally the minimal host speed of the third interval (high-speed-interval, see Figure 6(c)) is set to 70 km/h. Figure 7 shows the false-alarm-rate of all networks relative to the total number of emitted warnings.

B. Discussion

The results demonstrated in Figure 6 and Figure 7 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 0.6 s. Analogously, N_{auto} provides satisfying detection rates in terms of high velocities detecting all vehicles and even 93.1% within 0.3 s. 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.

C. Prospect

As a start the results of the neural network approach at hand show promise. Since every network has its strengths in particular situations, there are several possibilities for future investigations. Although the one-size-fits-all network provides a solid overall performance the training of different networks for several situations is preferred since the specialized networks provide even better detection rates for their particular strengths within less reaction time. Since it is possible to detect the actual traffic situation via odometry and curvature information, a deeper analysis of this approach

is intended.

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.

REFERENCES

- [1] S. Thrun, "Winning the darpa grand challenge," in *Knowledge Discovery in Databases: PKDD 2006*, ser. Lecture Notes in Computer Science, J. Fürnkranz, T. Scheffer, and M. Spiliopoulou, Eds. Springer Berlin / Heidelberg, 2006, vol. 4213, pp. 4–4, 10.1007/11871637-4. [Online]. Available: <http://dx.doi.org/10.1007/11871637-4>
- [2] A. Petrovskaya and S. Thrun, "Model based vehicle detection and tracking for autonomous urban driving," *Autonomous Robots*, vol. 26, pp. 123–139, 2009, 10.1007/s10514-009-9115-1. [Online]. Available: <http://dx.doi.org/10.1007/s10514-009-9115-1>
- [3] K. Macek, D. Vasquez, T. Fraichard, and R. Siegwart, "Safe vehicle navigation in dynamic urban scenarios," in *Intelligent Transportation Systems, 2008. ITSC 2008. 11th International IEEE Conference on*, oct. 2008, pp. 482–489.
- [4] S. Kolski, D. Furgeson, C. Stachniss, and R. Siegwart, "Autonomous driving in dynamic environments," in *Workshop on Safe Navigation in Open and Dynamic Environments at the IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS)*, Beijing, China, 2006.
- [5] M. Ye, J. Wu, and Y. Xiu, "Research of driver assistance system based on pervasive computing," in *Computer-Aided Industrial Design Conceptual Design, 2009. CAID CD 2009. IEEE 10th International Conference on*, Nov. 2009, pp. 2342–2344.
- [6] M. Ma, J. Chen, and G. Xu, "Research on adaptive road control algorithms of anti-lock braking system," in *Computer-Aided Industrial Design Conceptual Design, 2009. CAID CD 2009. IEEE 10th International Conference on*, Nov. 2009, pp. 2238–2240.
- [7] W.-J. Park, B.-S. Kim, D.-E. Seo, D.-S. Kim, and K.-H. Lee, "Parking space detection using ultrasonic sensor in parking assistance system," in *Intelligent Vehicles Symposium, 2008 IEEE*, June 2008, pp. 1039–1044.
- [8] C. Gearhart, A. Herold, B. Self, C. Birdsong, and L. Slivovsky, "Use of ultrasonic sensors in the development of an electronic travel aid," in *Sensors Applications Symposium, 2009. SAS 2009. IEEE*, Feb. 2009, pp. 275–280.
- [9] X.-T. Le, S.-B. Oh, W.-S. Lee, C.-S. No, and S.-H. Han, "Design of intelligent mobile robot system based on ultrasonic sensors," in *Control, Automation and Systems, 2007. ICCAS '07. International Conference on*, Oct. 2007, pp. 72–76.
- [10] V. Magori, "Ultrasonic sensors in air," in *Proc. IEEE Int. Ultrasonics Symp. (Cannes)*, 1994, pp. 471–81.
- [11] —, "Signal processing for smart ultrasonic sensors," in *CompEuro '89, 'VLSI and Computer Peripherals. VLSI and Microelectronic Applications in Intelligent Peripherals and their Interconnection Networks', Proceedings.*, May 1989, pp. 3/21–3/26.
- [12] J. Wang, G. Bebis, and R. Miller, "Overtaking vehicle detection using dynamic and quasi-static background modeling," in *Computer Vision and Pattern Recognition - Workshops, 2005. CVPR Workshops. IEEE Computer Society Conference on*, June 2005, p. 64.
- [13] P. Batavia, D. Pomerleau, and C. Thorpe, "Overtaking vehicle detection using implicit optical flow," in *Intelligent Transportation System, 1997. ITSC '97, IEEE Conference on*, Nov 1997, pp. 729–734.
- [14] C. Connette, J. Fischer, B. Maidel, F. Mirus, S. Nilsson, K. Pfeiffer, A. Verl, A. Durbec, B. Ewert, T. Haar, and D. Grödl, "Rapid detection of fast objects in highly dynamic outdoor environments using cost-efficient sensors," *accepted for the ROBOTIK 2012 conference in Munich*, 2012.
- [15] C. Goerick, D. Noll, and M. Werner, "Artificial neural networks in real-time car detection and tracking applications," *Pattern Recognition Letters*, vol. 17, no. 4, pp. 335–343, 1996. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/0167865595001298>
- [16] U. Handmann, T. Kalinke, C. Tzomakas, M. Werner, and W. Seelen, "An image processing system for driver assistance," *Image and Vision Computing*, vol. 18, no. 5, pp. 367–376, 2000. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S0262885699000323>