Proceedings of the
2007 IEEE Intelligent Vehicles Symposium
Istanbul, Turkey, June 13-15, 2007

A Real Time Object Detection Approach Applied to Reliable Pedestrian Detection

Guanglin Ma*, Su-Birm Park†, Alexander Ioffe‡, Stefan Müller-Schneiders† and Anton Kummert*

*Faculty of Electrical Information and Media Engineering
University of Wuppertal
D-42119 Wuppertal, Germany
{guanglin.ma, kummert}@uni-wuppertal.de

† Delphi Delco Electronics Europe
Advanced Engineering
D-42119 Wuppertal, Germany

‡ Delphi Deutschland GmbH
Body & Security Electronics
D-51674 Wiehl, Germany

{su-birm.park, alexander.ioffe, stefan.mueller-schneiders}@delphi.com

Abstract— **This paper presents a robust real time obstacle and pedestrian detection algorithm, which is capable of handling the challenges of stationary as well as moving objects, utilizing a single car mounted monochrome camera. First, the system detects obstacles above the ground plane by obtaining a "virtual stereo system" through the usage of inverse perspective mapping. A fast digital image stabilization algorithm is used to compensate erroneous detections whenever the flat ground plane assumption is an inaccurate model of the road surface. Finally, a low level pedestrian segmentation algorithm is developed to extract bounding boxes of potential pedestrians. Furthermore a novel approach called the Pedestrian Detection Strip is used to improve the calculation time by a factor of six compared to previous attempts. Experiments have been carried out by applying the proposed algorithm on prerecorded sequences as well as within a test vehicle and thus in a closed loop environment. The experimental results indicate a promising detection performance. Obstacles and pedestrians up to 50 meters away from the vehicle have been detected reliably at 64 frames per second on a 3GHz PC.**

I. INTRODUCTION

In the last years, the concept of a "sensing car" becomes one of the main directions of the electronics and algorithm development in the automotive industry, enclosing applications such as lane departure warning, park assistant, traffic sign recognition, etc. Some applications of the "sensing car", based on camera hardware, require the development of robust image processing algorithms for the detection and classification of critical situations outside and inside the car. For this, a very important part is the correct classification of human movement based on special features of the human body and faces [1]. Especially, the pre-impact pedestrian classification leads to a decrease of impact consequences for all participants by appropriate countermeasures.

An important preprocessing step for pedestrian classification is a computational time efficient detection of image regions supposing to include pedestrians, which decreases the computational requirements in all and contributes to robust real-time classification software.

Purely vision-based pedestrian detection is one of the most challenging tasks for object detection: pedestrians may move in different poses with variable intention and speed, pedestrians may walk in a group or carry items with them, they may wear differently with different color and patterns. All of these make a broad variability of their shape. Furthermore pedestrians may appear in numerous positions in the driving environment. Situations become more critical for non moving pedestrian. Stationary pedestrians are usually more difficult to distinguish from the background and optical flow based detection algorithms do not work in this case. An even more challenging task is the detection using a non-stationary camera, e.g., a camera mounted on a moving vehicle. In this case the conventional background subtraction methods completely fail because of the variety of depths changes from frame to frame.

There are two common approaches for obstacle detection by means of image processing: single camera based detection and two (or multiple) camera based detection (stereo vision based detection).

The single camera approach utilizes techniques like object model fitting [2], color segmentation [3], the detection of specific characteristics such as texture [4] or symmetry axes [5], or optical flow [6]. Inverse perspective mapping, which is based on the assumption of moving on a flat road has also been applied to obstacle detection [7]- [13]. In all of the approaches mentioned above, the estimation of 3D characteristics is done after the detection stage. The estimation is usually performed through a combination of knowledge about the objects (such as size), assumptions about the characteristics of the road and knowledge about the camera parameters through calibration. In [3] a color CCD mono camera is mounted on an agricultural vehicle for obstacle detection, whereby a different color distribution of a field track and obstacles is used for detection.

The stereo-vision-based detection is a well-known technique for directly obtaining three-dimensional (3-D) depth information of objects seen by two or more video cameras from different viewpoints [14]- [19]. In [19] a method for pedestrian (obstacle) detection is presented, whereby a system containing two stationary cameras is used. The

1-4244-1068-1/07/$25.00 ©2007 IEEE.

obstacles are detected by eliminating the ground surface by transformation and matching the ground pixels in the images of both cameras. The stereo-vision-based approaches have the advantage of directly estimating the 3D coordinates of an image feature, this feature being anything from a point to a complex structure. The difference of the viewpoint positions causes a relative displacement, called disparity, of the corresponding features in the stereo images. The search for correspondences is a difficult, time demanding task, which is not free from the possibility of errors. Obstacle detection techniques involving stereo-vision use different approaches in order to make some simplifications of the classic problem and achieve real-time capabilities [18]- [22].

The pre-classification algorithm has to detect pedestrians as a subset of obstacles appearing in front of the vehicle. In this paper, the detection step is performed by an obstacle detection algorithm, which satisfies the requirements of pedestrian detection (pedestrians can be considered as a subset belonging to an obstacles set). Otherwise, detection results themselves yield the information about possible hit targets usable for different warning applications. For a computing time effective classification, a certain detection of obstacles avoiding a false detection of color and lighting gradients on the lane is a key to the success of the whole application.

In the algorithm presented here, the detection has to be performed using a moving mono gray value camera system, which has substantial disadvantages (moving mono system) comparing to the system in [19] (stationary stereo system) and [3] (color system, applied only for field tracks). In this paper we present an algorithm using the ego motion of the mono camera to produce a "virtual" stereo system for background subtraction.

The purpose of the algorithm being developed by Delphi is the detection of pedestrians in urban traffic situations, using a mono camera system mounted inside a vehicle, at the top of the windshield. This camera system is used by additional applications, such as lane departure warning or forward collision warning. The multiple use of the same hardware contributes to the general demand to reduce the system costs.

II. Inverse perspective projection based obstacle detection

The principle of inverse perspective mapping based obstacle detection is to remove the perspective effect when the acquisition parameters (camera position, orientation, focal length,...) are known and when a good assumption about the road surface, e.g. the flat road hypothesis [23] can be made. In our work the flat road hypothesis is the only assumption needed in order to do obstacle detection. A fast image stabilization method is applied to compensate the noisy detection caused by the pitching and rolling of the host vehicle or by the unevenness of the road.

A. Perspective Projection and Inverse Perspective Projection

Any point in the image plane, which is located above a point P is a projection from a point in the world coordinates

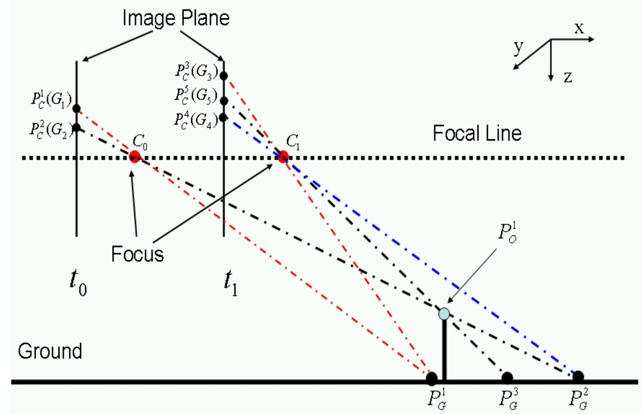


Fig. 1: An illustration of the proposed detection principle.

located below the horizon. These points in the image plane can be back projected onto the ground plane. The 3D world coordinates are described according to the SAE (Society of Automotive Engineers) standard coordinate system. As the origin of the coordinate system we choose the focal point of the camera.

A point $(x_w, y_w, z_w)^T$ in the world coordinates can be expressed by $(x_w, y_w, z_w, 1)^T$ in the homogeneous coordinates. The projection of this point from the world coordinates to the image coordinates can be expressed by

$$(x_i', y_i', z_i', 1)^T = H \cdot (x_w, y_w, z_w, 1)^T \tag{1}$$

where H is the transformation matrix from the world coordinates to the image coordinates. The transformation matrix H consists two sub steps:1) Projection of a point from the ground plane to a virtual camera plane which is perpendicular to the horizon. 2) Rotation of the virtual camera plane to the real camera plane. The final image coordinate is given by

$$(x_i, y_i)^T = \frac{1}{z_i'} (x_i', y_i')^T \tag{2}$$

The inverse projection from the camera coordinates to the world coordinates can simply be obtained by using the inverse of the projection matrix: H^{-1}. Please see [12] for a detailed description of the transformation matrix H.

B. Inverse Perspective Mapping based Detection

The principle of the proposed detection algorithm is illustrated in Fig. 1, where a side view of the image plane at different time steps t_0 and t_1 is shown. Let C_0 denote the camera's optical center at time t_0 where an image frame is taken by the camera and C_1 be the corresponding point at time t_1 where the second image frame is taken. Within the time interval $\Delta t = t_1 - t_0$ the camera moves from point C_0 to the point C_1 with the velocity v and yaw rate ω. The movement from point $C_0 = (x_0, y_0, z_0)^T$ to point $C_1 = (x_1, y_1, z_1)^T$ can be calculated as:

$$\begin{pmatrix} x_0 \\ y_0 \\ z_0 \end{pmatrix} = M \cdot \begin{pmatrix} x_1 \\ y_1 \\ z_1 \end{pmatrix} \tag{3}$$

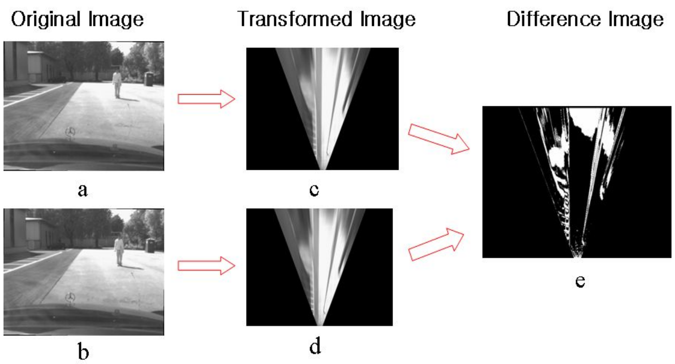


Fig. 2: Detection by performing differencing of transformed images.

Fig. 3: Detection with artifacts generated by the ego-motion of the host vehicle.

Fig. 4: Reduction of artifacts by means of image stabilization.

where M is a linear transformation matrix of points on the ground plane using the velocity and yaw rate of the host vehicle. For the sake of simplicity, the camera sensor plane is assumed to be perpendicular to the horizon and the rotation factor is set to zero (i.e. the rotation matrix is I).

Let point P_G denote points on the ground plane where $P_G = (X,Y,0)^T$ and P_O denote points belonging to an obstacle which is located above the ground plane where $P_O = (X,Y,Z)^T$ and $(Z < 0)$. At time t_0, the point P_G^1 on the ground plane is projected onto point P_C^1 on the camera plane through the focal point C_0. In this case the intersection of the optical ray $\overline{C_0P_G^1}$ with the ground plane is obviously P_G^1 itself. The gray value of the point P_C^1 is denoted by G_1 which is identical to the gray value of the point P_G^1 on the ground. For the point P_O^1 which is belonging to an obstacle above the ground plane, the projection onto the camera plane results in P_C^2. Note that now the intersection of ray $\overline{C_0P_O^1}$ with the ground plane is P_G^2. The gray value of the point P_C^2 is G_2 which is originating from the point P_O^1 on the obstacle. At time t_1, the projection of the point P_G^1 on the camera plane is P_C^3 (gray value G_3) and the intersection of the ray $\overline{C_1P_G^1}$ is still P_G^1 itself. Assuming a small time shift between consecutive image frames (which means the lighting changes during this time is negligible), the gray value at the position P_G^1 does not change between time t_0 and t_1 and thus, this gray value is eliminated by the background subtraction.

This is not the case for the point P_O^1 belonging to an obstacle. For the point P_C^2 at time t_0, the corresponding point at time t_1 is P_C^4 which is projected from P_G^2 on the ground plane with the gray value G_4. In contrast, the gray value G_4 of the point P_C^2 is from the point P_O^1 on the obstacle. After performing background subtraction, the gray value difference will be non-zero. It can be seen, that the distance between the points P_G^2 and P_G^3 increases with the height. Near the bottom of standing objects, this distance goes to zero - this is the point where the obstacle is "standing" on the road. After defining this point for the detected obstacle, its position on the road can be estimated using the "land map" coordinates.

The overall detection process is depicted in Fig. 2. In the figure, 2(a) and 2(b) are the captured images at the time steps t_0 and t_1, respectively. (c) and (d) are the corresponding projections of (a) and (b) on the ground plane. As mentioned above, only parts of the image located above the projection of the horizon can be projected to the ground plane. Since the size and shape of projected pixels on the ground plane is depending on the distance, the overall shape of the projected image on the ground plane is trapezoidal rather than rectangular. Finally, the transformed images at time t_1 and t_0 are subtracted and binarized in order to detect obstacles above the ground. In this step the ego motion of the car needs to be taken into account. Fig. 2(e) shows the binarized detection result on the ground plane.

C. Fast Digital Image Stabilization

It has been previously mentioned, that we rely on the assumption of an ideal ground plane (i.e. the ground plane is even and horizontal). In case this assumption is not a good model for the actual road, the detection result will contain unwanted artifacts. Additionally, pitching and rolling of the car will also result in detections which are not corresponding to real world objects. Fig. 3 shows this kind of detection artifacts. In the figure, detections resulting from the frame differencing process are marked in green. Note that the spatial location of the left curb is inaccurate and also some ground in the left side and end of the road is erroneously detected as obstacle. Unexpected detections on the right hand side of the road occur, since the real world structures are located significantly above the assumed ground plane level.

In order to compensate for the detection artifacts caused by the pitching of the vehicle, a novel fast 2D image stabilization approach is used. The idea is an extension of the work presented by Yeni and Ertürk in [24]. Instead of performing image stabilization directly on two consecutive images as proposed in [24], we first transform the image at time t_0 to the corresponding position at time t_1 utilizing the inverse perspective projection and the known vehicle motion parameters, namely speed and yaw rate. Afterwards the stabilization is done on time instance t_1. In this way, first the known vehicle motion is compensated and image stabilization needs only to be performed in order to compensate

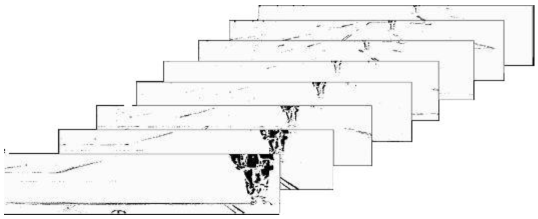
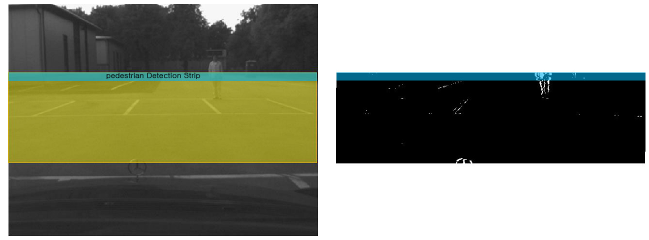
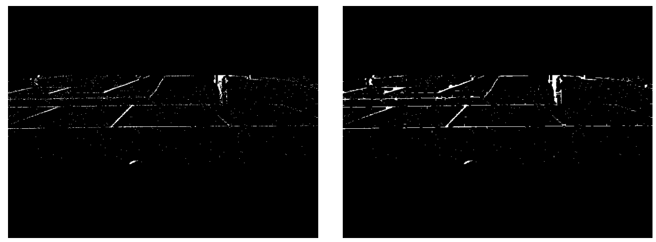


Fig. 5: Illustration of the basic idea which leads to the development of the Pedestrian Detection Strip.

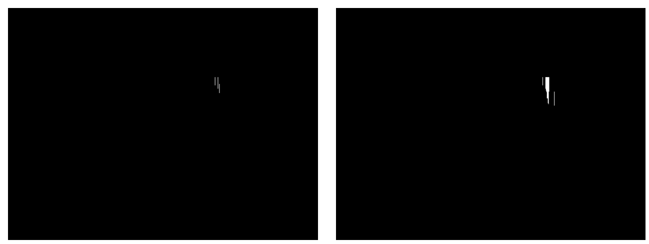


(a) original image (b) detection

Fig. 6: Detection with Pedestrian Detection Strip



(a) Detection (b) horizontal + vertical closing



(c) vertical opening of (a) (d) vertical opening of (b)

Fig. 7: Morphological operations

the effects caused by pitching or ground unevenness, etc.

Fig. 4 shows the corresponding detection result. Compared to the detection results without stabilization (Fig. 3), now the detection of the curb exactly matches its real position and additionally less detections appears on the left hand side and the end of the road.

III. Fast low level pedestrian segmentation

The proposed algorithm detects every obstacle which is standing above the ground under the assumption that the road is flat. Further processing steps are needed to filter out objects being sought (e.g., pedestrian, vehicle, etc.) from the initial detection results. As a preprocessing component of a pedestrian detection system the segmentation module has to prepare pedestrian candidates for feature extraction and classification steps. Since feature extraction and classification algorithms are time consuming tasks, the detection and segmentation modules should gain as much time as possible for further processing.

In our algorithm, we use a novel idea called Pedestrian Detection Strip (PDS) to reduce the time needed for the detection and segmentation steps. Additionally, we use a vertical direction oriented low level segmentation algorithm to search for pedestrian candidates within the detection results without too much time effort. Most false positive segments are cause by vertical objects like poles or trees. However, these false positive segments can be easily rejected by the succeeding classification module.

A. Pedestrian Detection Strip

Fig. 5 shows the detection results for a sequence of images showing a single pedestrian at different distances from the host vehicle using the proposed detection algorithm. As we can see from the detection results, the adult pedestrian is always located close to the horizon of the scene, independently from its distance to the car. Thus, in order to drastically reduce the calculation time, we only apply the detection algorithm to an image sub-region of 30 pixels height, which is located below the horizon as illustrated in Fig. 6. The height of 30 pixels has been chosen in order to detect a pedestrian in 50 meters distance from the car, given the camera parameters of the test vehicle. A pedestrian in 50 meters distance occupies around 15 pixels in height in the PDS and thus will not be eliminated by the Morphological Operations.

Due to afore mentioned location of the PDS, small children appearing at close distance in front of the host vehicle will not be detected. To tackle this issue, a second PDS in the lower part of the image can be used to detected children and small pedestrians.

B. Segmentation based on Morphological Operations

Due to the unevenness of the ground plane and the unknown motion of the camera, the detection results typically look like those shown in Fig. 7(a): Undesired single noise-like detections are clearly visible in the figure and additionally lane markers on the ground are partially detected. Although some of these artifacts can be compensated by means of image stabilization (see section II-C) and also the detection of lane markers can be suppressed by using a PDS located at the horizon, still a noise elimination step is needed in order to generate robust detection results.

In our work, horizontal and vertical morphological operators have been used to eliminate horizontal artifacts and small blobs together with noise. Simultaneously, detections in vertical direction are emphasized since usually pedestrians are highly vertical oriented compare to other obstacles. Only highly vertical oriented blobs remain after the morphological operations. These blobs are the final candidates for the segmentation of pedestrians.

C. Foot Point Search and Region of Interest Selection for Pedestrian Candidates

For each candidate blob, which has been detected according to Sec. III-B, a region of interest (ROI) is defined which completely surrounds the potential pedestrian. A binarized edge image of the defined ROI is calculated by using the Sobel edge detection operator and by applying a threshold afterwards. Starting from the lowest point of the detected blob, a downward connectivity search is applied on the binarized edge image. The end point of the downward connective search is our final foot point of the pedestrian candidate (see also Fig. 8).

Next, the foot point found is transformed to the ground plane under the assumption that the ground is flat. Attached to the transformed foot point on the ground plane a 1.8 meter high and 0.9 meter wide bounding box is defined and the defined bounding box is back transformed to the image plane again. This way the final ROI for the pedestrian is defined on the image plane.

Fig. 8: Illustration of the foot point search

IV. Experimental results

Running on a 3GHz PC the proposed algorithm is capable of processing 64 frames per second and can thus be considered as an extremely fast approach. Note that this processing speed is for the detection algorithm only, i.e. the classification and tracking modules have been disabled during the measurement. The images are captured by a VGA camera mounted on the windshield of the host vehicle. The captured images are delivered to the system via the CAN-BUS together with host movement data (i.e. yaw rate and velocity). We tested the system for a large variety of driving scenarios, both, offline as well as inside the vehicle in a closed loop mode (driving speed was typically up to 50kph). During the offline testing more than 50,000 frames showing pedestrians have been processed.

Fig. 9 presents some of the experimental results. From the examples it can be seen that most pedestrians are detected reliably and that only a small number of false positives exists. Most of the false positives are caused by vertical obstacles like poles or trees which have similar visual properties as pedestrians. A small number of false positives is not critical since they will be eliminated in the subsequent classification step.

In Fig. 9(a), Fig. 9(c) and Fig. 9(i) crossing pedestrians at close distance are detected correctly. Also pedestrians far away in Fig. 9(a) are detected correctly. Some false positives occur in both examples.

In Fig. 9(b) both pedestrians are detected correctly. However, several bounding boxes are drawn on the pedestrian on the right hand side. This is caused by multiple detections and inaccurate segmentations. A symmetry search and merging algorithm is under development for this case. Non-walking pedestrians in Fig. 9(d) are detected correctly. A small child on a bicycle is also detected but the bounding box is too large for it because the bounding box is calculated based on the assumption that the detected pedestrian is 1.8 meter high. In order to improve this issue, a head point search could be applied.

Pedestrians on bicycles are detected correctly in Fig. 9(e)(g)(i) and (j). In all three examples cars in the scene are also detected because they are also obstacles above the ground plane with vertical edges on it. Because our segmentation algorithm is focused on pedestrians, the bounding boxes for the cars do not match with the corresponding real world sizes. In Fig. 9(j) two pedestrians about 50 meters away are also detected correctly. The example here shows that our detection algorithm can easily be converted to detect vehicles by simply adapting the segmentation algorithm.

In Fig. 9(f) one adult and two children on the right hand side are correctly detected despite the fact that they are walking in a group and that only their back is visible. Three false positives are on the left hand side which are caused by the distant poles. Mis-detections occur in Fig. 9(h) due to the low contrast in the image. Note also that some bounding boxes are not centered correctly.

V. Conclusions

In this paper an inverse perspective mapping based pedestrian detection algorithm has been presented. The algorithm has been tested in a variety of driving scenarios using a test vehicle equipped with a monochrome VGA camera and industrial PC on it. A flat ground plane assumption is used within the proposed algorithm and a novel fast digital image stabilization algorithm is applied to compensate the wrong ground plane assumption. A novel pedestrian detection idea called ”Pedestrian Detection Strip” improves the calculation time by factor of six compared to previous attempts. At last a vertical oriented pedestrian segmentation algorithm is presented.

Experimental results show that the proposed detection algorithm delivers reliable results up to 50 meters in different driving situations. Most false positives occur on trees and poles along the roadside and can be easily eliminated through a subsequent classification process [25].

The described algorithm has been integrated in a vision based system by Delphi for various active safety applications like Pedestrian Protection, Pre-crash etc. The described algorithm has been integrated in a vision based system by

Delphi for various active safety applications like Pedestrian Protection, Pre-crash etc.

Fig. 9: Experimental results achieved with this system

REFERENCES

[1] D.M. Gavrila, "The Visual Analysis of Human Movement: A Survey", *Computer Vision and Image Understanding*, vol.73, no.1, pp.82-98, 1999.

[2] D. M. Gavrila, "Pedestrian Detection from a Moving Vehicle", *Proc. of European Conference on Computer Vision*, pp. 37-49, Dublin, 2000.

[3] E. Morimoto, M. Suguri, and M. Umeda. "Obstacle Avoidance System for Autonomous Transportation Vehicle based on Image Processing". *Agricultural Engineering International: the CIGR Journal of Scientific Research and Development*, Manuscript PM 01 009. Vol. IV., December 2002.

[4] T. Kalinke, C. Tzomakas, and W. von Seelen, "A Texture based Object Detection and an Adaptive Model-based Classification", *in Procs. IEEE Intelligent Vehicles Symposium '98*, pp. 341-346, Stuttgart, Germany, October 1998.

[5] A. Kuehnle, "Symmetry-based vehicle location for AHS', *in Procs. SPIE Transportation Sensors and Controls: Collision Avoidance, Trafic Management, and ITS*, vol. 2902, Orlando, FL, pp. 19-27, November 1998.

[6] Yan Zhang, Stephen J. Kiselewich, William A. Bauson, and Riad Hammoud, "Robust Moving Object Detection at Distance in the Visible Spectrum and Beyond Using A Moving Camera", *Proc. of the 2006 Conference on Computer Vision and Pattern Recognition Workshop*, 2006.

[7] M. Bertozzi, A. Broggi, and A. Fascioli, "Stereo Inverse Perspective Mapping: Theory and Applications", *Image and Vision Computing Journal*, 1998.

[8] M. Bertozzi, A. Broggi, and A. Fascioli, "An extension to the inverse Perspective Mapping to handle not-flat roads", *IEEE International Conference on intelligent Vehicles*, 1998.

[9] H.A. Mallot, H.H. Buelthoff, J.J. Little, and S. Bohrer, "Inverse perspective mapping simplifies optical flow computation and obstacle detection", *Biomedical and Life Sciences, Computer Science and Engineering*,Volume 64, Number 3 / January, 1991

[10] A. Broggi, M. Bertozzi, and A. Fascioli, "Self-Calibration of a Stereo Vision System for Automotive Applications", *Proceeding of the 2001 IEEE International Conference on Robotics & Automation*, 2001.

[11] H. Niemann, W. Kasprzka and P. Weierich, "Integrated motion and geometry based obstacle detection in image sequence of traffic scenes", *Proc. SPIE* Vol. 2736, p. 228-239, Enhanced and Synthetic Vision, 1996.

[12] R. M. Haralick, "Monocular Vision Using Inverse Perspective Projection Geometry: Analytic Relations", *IEEE Computer Society Conference on Computer Vision and Pattern Recognition(CVPR)*, 1989

[13] D. Baehring, S. Simon, W. Niehsen, C. Stiller, "Detection of close Cut-In and Overtaking Vehicles for Driver Assistance based on Planar Parallax", *Proceedings. IEEE Intelligent Vehicles Symposium*, 2005.

[14] R. Hartley and A. Zisserman, "Multiple View Geometry in Computer Vision.Cambridge", U.K.: Cambridge Univ. Press, 2000.

[15] O. Faugeras, "Three Dimensional Computer Vision". Cambridge, MA: MIT Press, 1993.

[16] M. Z. Brown, D. Burschka, and G. D. Hager, "Advances in computational stereo," *IEEE Trans. Pattern Anal. Machine Intel.*, vol. 25, pp. 993-1008, August 2003.

[17] S. Barnard and M. Fisher, "Computational stereo," ACM Comput. Surv., vol. 14, pp. 533-572, 1982.

[18] M. Bertozzi and A. Broggi, "GOLD: a Parallel Real-Time Stereo Vision System for Generic Obstacle and Lane Detection", *IEEE Trans. on Image Processing*, 7(1):62-8 1, January 1998,

[19] K. Onoguchi, Shadow elimination method for moving object detection, *Fourteenth International Conference on Pattern Recognition, Brisbane*,Proceedings, vol.1, pp. 583-587, Qld., Australia, August 1998.

[20] U. Franke, D. M. Gavrila, S. Gorzig, F. Lindner, F. Paetzhold and C. Wohler, "Autonomous Driving Approaches Downtown", *IEEE Intelligent Systems*, vo1.13, nr.6, pp. 40- 48, 1998.

[21] T. A. Williamson, "A high-performance stereo vision system for obstacle detection", *CMU-RI-TR- 98-24*. Robotics Institute Carnegie Mellon University. Pittsburg, PA 15123, September 25, 1998.

[22] M. Bertozzi, A. Broggi, A. Fascioli, and S. Nichele, "Stereo Vision-based Vehicle Detection", *in Proc. IEEE Intelligent Vehicles Symposium*, pages 39-44, Detroit, USA, October 2000.

[23] M. Bertozzi, A. Broggi, and A. Fascioli. "An extension to the Inverse Perspective Mapping to handle non-flat roads". *In Proc. IEEE Intelligent Vehicles Symposium*, pages 305-310, Stuttgart, October 1998.

[24] Yeni. A., Ertürk. S., "Fast Digital Image Stabilization using One Bit Transform Based Sub-Image Motion Estimation", *IEEE Transactions on Consumer Electronics*, 51, (3), 917-921, August 2005.

[25] S. Schauland, A. Kummert, S.B. Park, U. Iurgel and Y. Zhang, "Vision-based Pedestrian Detection : Improvement and Verification of Feature Extraction Methods and SVM-based Classification", *Proceedings of the IEEE ITSC 2006*,Toronto, Canada, September 17-20, 2006