Systematic Literature Review for Passive Vision Road Obstacle Detection

Authors:
Thiago Rateke
Aldo von Wangenheim

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Summary in English

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1 INTRODUCTION

One of the most important tasks in a visual perception system for navigation is the perception of the environment and the obstacles contained in this environment. So a robust intelligent vehicles system must raise the necessary information for the obstacles detection and tracking, such as: position, size and speed that each obstacle detected has (DANESCU et al., 2012).

Many vision-based obstacle detection methods aim to identify only certain types of obstacles, such as only cars or pedestrians only. This can lead to systems with a considerable number of false detection alarms that lose obstacles that should be detected (WON; JUNG, 2012).

Currently the cases of great prominence in the autonomous navigation use diverse sensors, not only camera (URMSON et al., 2008), (URMSON, 2014b), (URMSON, 2014a) e (FERNANDES et al., 2014). And one of these sensors, and perhaps the main one, is LIDAR (Light Detection and Ranging), which is an optical laser used for remote sensing of reflected light properties, in order to measure distances between the sensor and the target object (LIDAR, 2015). In the mentioned projects, LIDAR is considered Class1, which is the category with the lowest impact and with wavelengths of 905nm.

In (GROUP SAFETY PUBLICATION. INTERNATIONAL STANDARD, 2001) e (STANDARD, 2005) it is said that Class1 lasers, when they do not have direct contact with the human eye during a longer period, pose no danger to the retina. However, in (GROUP SAFETY PUBLICATION. INTERNATIONAL STANDARD, 2001) they present a table with the categorization of the lasers and the possible risks with the excess of exposure in each one of the levels. Lasers with a wavelength between 780nm and 1400nm, which is the range of LIDAR, can cause cataracts and burn the retina. Thus, if autonomous vehicles becomes a daily reality, LIDAR may not be a safe solution for a large number of vehicles because of unprotected over-exposure.

Passive Vision (PV) may be an alternative in this future scenario and researchs using this approach, using only the camera information (captured image) is done over a long period of time. However, they are usually tested on good quality asphalt roads (usually in North America or Europe), and leave aside other problems that are found in low quality and poor road maintenance scenarios, such as: puddles and potholes.

This review intends to analyze the state of the art for obstacles detection in a vehicular navigation scenario, using only the image information, with frontal and horizontal captures (or close to horizontal) and which can be applied in: Simultaneous Localization and Mapping (SLAM) systems, and mainly in Advanced Driver-Assistance systems (ADAS) and Autonomous
Navigation systems.

This review is conducted as a Systematic Literature Review (SLR), with procedures described in (KITCHENHAM; CHARTERS, 2007). The SLR is divided into three phases: 1) Definition, where the research objectives are identified and a protocol is defined, specifying the procedures, databases and inclusion and exclusion criteria. 2) Execution, step that includes the search and selection of the relevant works according to the protocol established in the definition stage. 3) Analysis, final step, which consists of the analysis of each work selected in the execution stage within the objectives defined for SLR.

Our goal is to analyze the methods that are being used, what kind of obstacles are being detected in the navigation scenario, and if they distinguish possible faults or changes on the road surface, such as: potholes, craters, shadows, cracks and puddles. We also want to check if the published papers are dealing with the problems caused by shadows, after all the shadow of an object should not be considered as an obstacle.
2 SYSTEMATIC LITERATURE REVIEW

**Question:** What is the state of the art in road obstacle detection, using passive vision?

**Population:** Works on road obstacle detection, using computer vision, available in electronic libraries.

**Intervention:** Analysis of the state of the art in road obstacle detection.

**Results:** Comparison of road obstacle detection works.

**Context:** Digital libraries: ACM Digital Library, IEEE Xplore, Science Direct and Springer Link.

2.1 SEARCH DEFINITIONS

The details of the search definition, such as: search locations, terms, inclusion and exclusion criteria, are presented in Table 1.

<table>
<thead>
<tr>
<th>Search Locations</th>
<th>Search Terms</th>
</tr>
</thead>
<tbody>
<tr>
<td>- ACM Digital Library;</td>
<td>- road obstacle detection;</td>
</tr>
<tr>
<td>- IEEE Xplore;</td>
<td>- road obstacle tracking;</td>
</tr>
<tr>
<td>- Science Direct;</td>
<td>- obstacle detection.</td>
</tr>
<tr>
<td>- Springer Link.</td>
<td></td>
</tr>
</tbody>
</table>

**Inclusion criteria**

- Papers written in English language;
- Papers published between 2007 and 2017;
- Papers that present an obstacle detection approach;
- Works with frontal images and with horizontal (or near) view of the road;
- Works that use only passive vision and digital image processing and computer vision methods (jobs that use other sensors together will be accepted if the passive vision step is well separated and presents an obstacle detection result).

**Exclusion Criteria**

- Short papers, such as abstracts or expanded abstracts;
- Obstacles Detection in indoor environments (blind guides, cleaning machines, factories machines).
2.2 SEARCH EXECUTION

Initially the selection resulted in 1777 papers and an analysis by titles, abstracts, keywords and images was performed resulting in 110 papers. The execution of the search is presented in the following tables: Table 2, Table 3, Table 4 and Table 5.

Table 2 – Path Detection - ACM Execution

<table>
<thead>
<tr>
<th>ACM Digital Library</th>
<th>Search String</th>
<th>Refining the Search</th>
<th>Results Quantity</th>
</tr>
</thead>
</table>
|                     | acmdltltle: (“road obstacle detection” OR “road obstacle tracking” OR “obstacle detection”) OR recordAbstract: (“road obstacle detection” OR “road obstacle tracking” OR “obstacle detection”) OR keywords.author.keyword: (“road obstacle detection” OR “road obstacle tracking” OR “obstacle detection”) | - Date: Published since - 2007;  
- Format: Content Formats - PDF; | 33    | Selected | 4 |

Table 3 – Path Detection - IEEE Execution

<table>
<thead>
<tr>
<th>IEEE Xplore</th>
<th>Search String</th>
<th>Refining the Search</th>
<th>Results Quantity</th>
</tr>
</thead>
</table>
|             | ((((((( (“Document Title”: “road obstacle detection”) OR “Abstract”: “road obstacle detection”) OR “Author Keywords”: “road obstacle detection”) OR “Document Title”: “road obstacle tracking”) OR “Abstract”: “road obstacle tracking”) OR “Author Keywords”: “road obstacle tracking”) OR “Document Title”: “obstacle detection”) OR “Abstract”: “obstacle detection”) OR “Author Keywords”: “obstacle detection”))) | - Date: 2007-2017;  
- Content Type: Journals & Magazines and Conference Publications. | 994    | Selected | 76 |
Table 4 – Path Detection - Science Direct Execution

<table>
<thead>
<tr>
<th>Science Direct</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Search String</strong></td>
</tr>
<tr>
<td>TITLE-ABSTR-KEY(“road obstacle detection”) or TITLE-ABSTR-KEY(“road obstacle tracking”) or TITLE-ABSTR-KEY(“obstacle detection”)</td>
</tr>
<tr>
<td><strong>Refining the Search</strong></td>
</tr>
<tr>
<td>- Areas: Computer Science;</td>
</tr>
<tr>
<td>- Date: pub-date &gt; 2006 and pub-date &lt; 2018;</td>
</tr>
<tr>
<td>- Content Type: Journals.</td>
</tr>
<tr>
<td><strong>Results Quantity</strong></td>
</tr>
<tr>
<td>46</td>
</tr>
<tr>
<td>Selected</td>
</tr>
<tr>
<td>8</td>
</tr>
</tbody>
</table>

Table 5 – Path Detection - Springer Execution

<table>
<thead>
<tr>
<th>Springer Link</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Search String</strong></td>
</tr>
<tr>
<td>(“road obstacle detection” OR “road obstacle tracking” OR “obstacle detection”)</td>
</tr>
<tr>
<td><strong>Refining the Search</strong></td>
</tr>
<tr>
<td>- Date: Date Published between 2007-2017;</td>
</tr>
<tr>
<td>- Area: Discipline - Computer Science;</td>
</tr>
<tr>
<td>- Language: English.</td>
</tr>
<tr>
<td><strong>Results Quantity</strong></td>
</tr>
<tr>
<td>704</td>
</tr>
<tr>
<td>Selected</td>
</tr>
<tr>
<td>22</td>
</tr>
</tbody>
</table>

The works of (HWANG; JI; KIM, 2012) and (COSTA et al., 2012) presented an approach to aid the visually impaired people. Although they are not in the context of vehicular navigation, they both meet search criteria, identify obstacles in external environments, with horizontal (or near horizontal) images. Therefore, both were kept in the papers selection. Likewise, the work of (KIM et al., 2015) and (YOO et al., 2016) were kept in this review, although they are aimed at applications in rear cameras in vehicles.

We have found a survey publication (BERNINI et al., 2014), being focused in stereo vision techniques. Thus, in addition to analyzing more recent work, our review intend to analyze more computer vision techniques to do the road obstacle detection task, and also to make an analysis based on results features.
3 PAPERS ANALYSIS

3.1 2007

3.1.1 Vision-based Pedestrian Detection - Reliable Pedestrian Candidate Detection by Combining IPM and a 1D Profile

**ID:** (MA et al., 2007) **Base:** IEEE

**Detection Target:** Pedestrian.

**Handles shadows:** Partially (according to the authors, does not show in the results).

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** Results in different weathers (fog and rain).


**Comments:** In this work they have done a pedestrian detection using a Inverse Perspective Mapping (IPM) to select the candidates. After that, they have applied a threshold to keep only the pedestrians. The focus is on vertical objects and a Sobel edge detection helps to find these vertical objects.

**Image:**

Figure 1 – (MA et al., 2007) results.

3.1.2 The Obstacle Detection Method using Optical Flow Estimation at the Edge Image

**ID:** (NAITO; ITO; KANEDA, 2007) **Base:** IEEE

**Detection Target:** Vehicles.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.
Other features: No.
Comments: Although they say that this work is for aims to do an obstacles detection in general, they only present few results (in fact, only one) and only with the detection of vehicles. To do this, they used Optical Flow after a corner detection to find the obstacles in the scene with only one camera. Depends on objects in the scene or the camera shooting are in motion.

Image:

Figure 2 – (NAITO; ITO; KANEDA, 2007) results.

3.1.3 A Global Optimization Algorithm for Real-Time On-Board Stereo Obstacle Detection Systems

ID: (KUBOTA; NAKANO; OKAMOTO, 2007) Base: IEEE
Detection Target: Obstacles in general.
Handles shadows: No.
Identifies puddles: No. Identifies potholes or damages: No.
Other features: They present some results at night and some with rain.
Comments: In this work an obstacle detection is made, without focus by obstacle types. Although only one obstacle result is presented other than a vehicle. They have used Stereo Vision. This makes it possible to make an estimate of the road plan. The disparity image is calculated, and then it finds
the edges in the disparity. The road parameters are found by Labayrade’s V-Disparity method. The focus is on detecting the lower edges of obstacles taking into account the road plan.

Image:

Figure 3 – (KUBOTA; NAKANO; OKAMOTO, 2007) results.

3.1.4 Obstacle Detection from IPM and Super-Homography

**ID:** (SIMOND; PARENT, 2007) **Base:** IEEE  
**Detection Target:** Obstacles in general (Focus on finding free space for navigation).  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Inverse Perspective Mapping (IPM). Super homography. Canny Edge Detection.  
**Comments:** An obstacle detection without focus on a specific type of obstacle is presented in this paper. However, the focus here is not exactly on obstacle detection itself, but on the detection of free spaces for navigation. To
do this, they have used an Inverse Perspective Mapping (IPM), super homography an Canny edge detection.

**Image:**

![Figure 4 – (SIMOND; PARENT, 2007) results.](image)

### 3.1.5 Monocular Vision Based Obstacle Detection for Robot Navigation in Unstructured Environment

**ID:** (SHEN; DU; LIU, 2007) **Base:** Springer  
**Detection Target:** Obstacles in general.  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Optical Flow. KLT feature tracker. Region of Interest (ROI).  
**Comments:** In this work an obstacle detection in general is presented. The scenery is not in road context, it is focused for robotic navigation. But is within the inclusion criteria of this review, with frontal camera and horizontal vision. To do the obstacle detection task they have applied an Optical Flow, KLT feature tracker and also use a Region of Interest (ROI). Evaluates camera rotation and focal expansion. Uses a nonlinear method to optimize focal rotation and expansion. And finally, an inverse contact time estimate is used.
3.1.6 Robust Obstacle Detection Based on Dense Disparity Maps

**ID:** (MILED; PESQUET; PARENT, 2007) **Base:** Springer  
**Detection Target:** Obstacles in general.  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Stereo Vision. Disparity Map. Segmentation.  
**Comments:** This work uses Stereo Vision to calculate a Disparity Map. It makes the segmentation of the objects based on the disparity map using surface orientation criteria. They do an obstacle detection in general. Despite showing few results, presents people and vehicles.

**Image:**

Figure 5 – (SHEN; DU; LIU, 2007) results.  

Figure 6 – (MILED; PESQUET; PARENT, 2007) results.
3.1.7 WarpCut - Fast Obstacle Segmentation in Monocular Video

**ID:** (WEDEL et al., 2007)  **Base:** Springer  
**Detection Target:** Obstacles in general.  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Graph cut segmentation. Region of Interest (ROI). Binary labeling.  
**Comments:** Here they present an obstacle detection without specific type, but most of the examples presented in the results are with vehicles. They segment the image into three parts: ground plane, background, and obstacles by a Graph cut segmentation. After they define a Region of Interest (ROI) where binary labeling is applied to refine the detection of obstacles.

**Image:**  
![Figure 7 – (WEDEL et al., 2007) results.](image_url)

3.1.8 Multi-cue Pedestrian Detection and Tracking from a Moving Vehicle

**ID:** (GAVRILA; MUNDER, 2007)  **Base:** Springer  
**Detection Target:** Pedestrian.  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Stereo Vision. Disparity Map. Region of Interest (ROI). Thresholds by Chamfer Distance. Thresholds by edge.  
**Comments:** In this work they present an approach in four modules: 1) Region of Interest (ROI) generation based on stereo vision information. 2) Shape-based detection. Here thresholds are applied by Chamfer distance and also by edge. 3) Classification based on texture. 4) Verification based on stereo vision information and cross-correlation. These steps are complemented by a tracking module.
3.2 2008

3.2.1 Contrast-invariant Obstacle Detection System using Color Stereo Vision

**ID:** (CABANI; TOULMINET; BENSRAIR, 2008) **Base:** IEEE
**Detection Target:** Obstacles in general.
**Handles shadows:** Yes (Nothing is said, but in the presented results the shadows are not considered as part of the obstacle).
**Identifies puddles:** No. **Identifies potholes or damages:** No.
**Other features:** No.
**Methods:** Stereo Vision. Disparity Map. Edge detection.
**Comments:** In this work they have done an obstacle detection without a spe-
cific target. They have used Stereo vision to compute the Disparity Map. And they detect obstacles by extracting edges of 3-D obstacles through the Disparity Map. They also have used a color slope operator for feature extraction.

**Image:**

![Image](image_url)

Figure 9 – (CABANI; TOULMINET; BENSRHAIR, 2008) results.

### 3.2.2 Obstacle Detection Using Virtual Disparity Image for Non-Flat Road

**ID:** (SUGANUMA; SHIMOYAMA; FUJIWARA, 2008) **Base:** IEEE  
**Detection Target:** Obstacles in general.  
**Handles shadows:** Yes (Nothing is said, but in the presented results the shadows are not considered as part of the obstacle).  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** Displays an example with vehicle detection inside a tunnel.  
**Methods:** Stereo Vision. V-disparity.  
**Comments:** Another obstacle detection without a specific target is presented in this paper. Here they estimate the road shape by Dynamic Programming and use this information to help to obstacle detection. They have used Stereo Vision techniques, mainly the V-Disparity information.
3.2.3 An Stereo Matching Approach to Detect Obstacle in ALV System

**ID:** (YONGQUAN et al., 2008) **Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.

**Methods:** Stereo Vision. Image Binarization. Segmentation.

**Comments:** This work detects obstacles by the following steps: 1) The image is binarized. 2) Binarized images are segmented. 3) Finally, the stereo matching between right and left capture images. A contour analysis of binarized images is also performed. They present few results (only two).
3.2.4 4-D Tensor Voting Motion Segmentation for Obstacle Detection in Autonomous Guided Vehicle

**ID:** (DUMORTIER; HERLIN; DUCROT, 2008) **Base:** IEEE
**Detection Target:** Obstacles in general.
**Handles shadows:** No.
**Identifies puddles:** No. **Identifies potholes or damages:** No.
**Other features:** No.
**Methods:** Tensor voting. Watershed segmentation. Labeling.
**Comments:** In this work a tensor voting structure extended to 4-D space is applied. Followed by a Watershed segmentation to get close edges. Then, the cells are grouped and labeled in relation to the rigidity restrictions of planar parallax. At last, a visual odometry based on texture learning and tracking is used. They have presented only few examples and only with vehicle detection.
3.2.5 Towards Optimal Stereo Analysis of Image Sequences

**ID:** (FRANKE et al., 2008) **Base:** Springer

**Detection Target:** Obstacles in general (Focus on finding free space for navigation).

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.


**Comments:** This work aims to identify obstacles in the scene to find the free space for navigation. To do this, Stereo Vision techniques are used, constructing a Disparity Map and applying an Occupancy grid based on this Disparity Map. At the end, a Kalman filter is applied that integrates stereo information as well as Optical Flow data.
Figure 13 – (FRANKE et al., 2008) results.

3.3 2009

3.3.1 Pedestrian detection using a single monochrome camera

**ID:** (MA et al., 2009b) **Base:** IEEE
**Detection Target:** Pedestrian.
**Handles shadows:** Partially.
**Identifies puddles:** No. **Identifies potholes or damages:** No.
**Other features:** No.
**Comments:** Continuation from (MA et al., 2007). Two different approaches if pedestrians are near or far. For the near ones a motion segmentation is applied. Points of interest are detected with the Harris corner detector and using the Kalman filter. A grouping by near neighbors is used to separate Regions
of Interest (ROI), using Ward’s distance. For distant, use Inverse Perspective Mapping (IPM) and follow the rest of the previous work.

**Image:**

![Image](image.png)

Figure 14 – (MA et al., 2009b) results.

### 3.3.2 A Real-Time Rear View Camera Based Obstacle Detection

**ID:** (MA et al., 2009a) **Base:** IEEE  
**Detection Target:** Obstacles in general.  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** Rear view.  
**Comments:** Also a continuation from (MA et al., 2007). They perform the detection based on motion (Optical Flow) and edge-based (Sobel). Road feature information are extracted and Fuzzy logic is used to color classification. They use the Hough transform to detect lines. This work is aimed at rear view cameras, but it is kept in this review because it is within the criteria, after all the capture is with horizontally images and the position is the same if it were frontal (it is not a diagonal image for example).
3.3.3 A Method of Stereo Obstacle Detection Based on Image Symmetrical Move

**ID:** (XU et al., 2009) **Base:** IEEE  
**Detection Target:** Vehicles.  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Stereo Vision. Cell of Interests (COIs).  
**Comments:** This work is focused on vehicle detection. They have presented an approach based on stereo vision. Also they have made a cell partition and done a Cell of Interest (COI) approach to calculate the obstacles.

![Figure 15 — (MA et al., 2009a) results.](image)

**Figure 16 — (XU et al., 2009) results.**
3.3.4 Moving Obstacle Detection in Highly Dynamic Scenes

**ID:** (ESS et al., 2009) **Base:** IEEE
**Detection Target:** Pedestrian.
**Handles shadows:** No.
**Identifies puddles:** No. **Identifies potholes or damages:** No.
**Other features:** No.
**Comments:** Focusing on pedestrian detection, this work makes use of stereo vision techniques and identifies the ground plane through V-disparity and Least-Median-of-Squares. They use a Bayesian Network to improve results. Visual odometry allow to place detected objects in a common world coordinate. Kalman filters assist in estimating the trajectory for tracking detected objects. The Histogram of Oriented Gradients (HOG) is also used to objects detection process. Inference is conducted using Pearl’s Belief Propagation.

![Image](image_url)

Figure 17 – (ESS et al., 2009) results.

3.3.5 Asynchronous stereo vision system for front-vehicle detection

**ID:** (CHIU et al., 2009) **Base:** IEEE
**Detection Target:** Vehicles.
**Handles shadows:** Yes.
**Identifies puddles:** No. **Identifies potholes or damages:** No.
**Other features:** Results at night and in rainy day.
**Methods:** Stereo Vision. Sobel edge detection. Region of Interest (ROI).

**Comments:** Vehicle detection is the focus of this work. First a vehicle detection is made by Sobel edge detection. The regions found are used as Region of Interest (ROI) for the depth calculation in these regions. A horizontal scan is done from the bottom to up. The problem with shadows is solved by the ROI symmetry both vertically and horizontally.

**Image:**

![Image](image)

Figure 18 – (CHIU et al., 2009) results.

### 3.3.6 Obstacle Detection Based on Occupancy Grid Maps From Virtual Disparity Image

**ID:** (KOHARA; SUGANUMA, 2009) **Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** Yes (Nothing is said, but in the presented results the shadows are not considered as part of the obstacle).

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.

**Methods:** Stereo Vision. Disparity Map. Occupancy Grid Maps.

**Comments:** In this work a detection of obstacles without distinction by type is made. An Occupancy Grid Maps is built based on the generated Disparity Map, which the authors say helps reduce detection errors. The cell grids are analyzed taking into consideration the state in the previous frames.
3.3.7 Stereovision-based 3D obstacle detection for automotive safety driving assistance

**ID:** (VENTROUX et al., 2009) **Base:** IEEE  
**Detection Target:** Vehicles.  
**Handles shadows:** No.  
**Identifies puddles:** No.  
**Identifies potholes or damages:** No.  
**Other features:** No.  
**Comments:** Vehicle detection is the focus of this work. To do this, they have used Stereo Vision techniques, taking care about all steps, like: image rectification, correction of distortions and finally the Disparity Map calculation. They also have used the Kalman filter to increase the performance. The V-Disparity data helps to find the obstacles also taking into account the road plane. Road space is represented by Hough Transform lines or by RANSAC.
3.3.8 Dense Stereo-Based ROI Generation for Pedestrian Detection

**ID:** (KELLER; LLORCA; GAVRILA, 2009)  
**Base:** Springer

**Detection Target:** Pedestrian.  
**Handles shadows:** No.  
**Identifies puddles:** No.  
**Identifies potholes or damages:** No.  
**Other features:** No.

**Comments:** Pedestrian detection is the focus of this work. They also have used the Stereo vision techniques, and a Region of Interest is defined based on the Disparity Map. Also a B-spline is used to define the road profile. The matching to pedestrian detection use the Chamfer distance and a defined threshold.
3.3.9 Moving Object Segmentation Using Optical Flow and Depth Information

**ID:** (KLAPPSTEIN et al., 2009)  **Base:** Springer

**Detection Target:** Obstacles in general.

**Handles shadows:** No.

**Identifies puddles:** No.  **Identifies potholes or damages:** No.

**Other features:** No.


**Comments:** Different techniques are applied to detect obstacles at work, such as: Stereo Vision, Optical Flow, and Graph cut segmentation to group the relevant features to certain detected objects. Finally, Kalman filters are used to improve the results. It depends on the obstacles being in motion to perform object detection.
3.4 2010

### 3.4.1 On-Road Vehicle detection by Cascaded Classifiers

**ID:** (HOTA; JONNA; KRISHNA, 2010) **Base:** ACM  
**Detection Target:** Vehicles.  
**Handles shadows:** No.  
**Identifies puddles:** No.  
**Identifies potholes or damages:** No.  
**Other features:** No.  
**Comments:** A cascade method of complex characteristics is proposed in the later phase of the cascade classifier to improve detection performance. The performance of local and global texture features in combination with high performance features is compared. The best performance for obstacles detection on the road is achieved by the Adaboost feature with Haar-like, along...
with the features of Support Vector Machine (SVM) and Histogram of Oriented Gradients (HOG). They focused on vehicle detection.

**Image:**

![Image](image.jpg)

Figure 23 – (HOTA; JONNA; KRISHNA, 2010) results.

### 3.4.2 Processing Dense Stereo Data Using Elevation Maps: Road Surface, Traffic Isle, and Obstacle Detection

**ID:** (ONIGA; NEDEVSCHI, 2010) **Base:** IEEE  
**Detection Target:** Obstacles in general.  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Dense Stereo Vision. Digital Elevation Maps. RANSAC.  
**Comments:** In this work is made the road detection and obstacles detection on the road. First a 3D reconstruction is done, through stereo density. The 3D data obtained from the stereo density are transformed into a Rectangular Digital Elevation Map. Two classifiers are proposed, one based on density and another based on road surface. The density-based obstacle classifier marks the cells as road or obstacle in the DEM, using the 3D density points as the criterion. A quadratic road surface model is initially adjusted by a Random Sample Consensus (RANSAC) method for the region in front of the vehicle. The road surface is used as discrimination between road points, traffic island, and obstacle. Finally, a merger and error filtering are performed on the results of the classifiers.
3.4.3 Background Subtraction and 3D Localization of Moving and Stationary Obstacles at Level Crossings

**ID:** (FAKHFAKH et al., 2010) **Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.


**Comments:** It depends on the obstacles being in motion. To do the obstacles detection, they start with a Background Subtraction and a Color Independent Component Analysis (CICA). They also have used Stereo Vision, and a Disparity Map is computed in moving pixels by Weighted Average Color Difference (WACD). The final classification is done by a Confidence Measure technique.
3.4.4 Real-time Obstacle Detection in Complex Scenarios Using Dense Stereo Vision and Optical Flow

**ID:** (PANTILIE; NEDEVSCHI, 2010) **Base:** IEEE  
**Detection Target:** Obstacles in general.  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Stereo Vision. Optical Flow.  
**Comments:** In this work the data fusion obtained by Stereo Vision and Optical Flow (by KLT tracker) techniques is made, combining the depth estimate with the motion estimation of the objects in the scene generating a depth-adaptive occupancy grid.
3.4.5 Moving Obstacle Detection using Cameras for Driver Assistance System

**ID:** (NISHIGAKI; ALOIMONOS, 2010)  
**Base:** IEEE  
**Detection Target:** Obstacles in general.  
**Handles shadows:** No.  
**Identifies puddles:** No.  
**Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Stereo Vision. Optical Flow. Color segmentation. Least median squares. RANSAC.  
**Comments:** It depends on the obstacles being in motion. Two algorithms for identifying obstacles in motion. The first algorithm checks the regions of obstacle movement looking for conflicts between the image and epipolar constraint when the obstacles move in a different direction regarding the cameras movement. The second algorithm finds the regions of motion by the disparities, especially when the object moves in the same direction as the cameras move. Also uses Optical Flow analysis and do a color segmentation. The accuracy of Optical Flow was improved by robust model fitting methods like: Least median squares and RANSAC.
3.4.6 Probabilistic representation of the uncertainty of stereo-vision and application to obstacle detection

**ID:** (PERROLLAZ; SPALANZANI; AUBERT, 2010) **Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.


**Comments:** In this work the authors also use information obtained by Stereo Vision techniques, but here the U-Disparity from the Disparity Map is used. They put this information in an Occupational Grids framework and also use Gaussian distribution for smoothing process.
3.4.7 Parallel Computation for Stereovision Obstacle Detection of Autonomous Vehicles Using GPU

**ID:** (XU; ZHANG, 2010) **Base:** Springer

**Detection Target:** Obstacles in general.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.

**Methods:** Stereo Vision. Census transform. Disparity Map.

**Comments:** In this paper they take care about all Stereo Vision process, such as: camera calibration, image rectification, and they have used the Census transform on the rectified images, construction of disparity map, 3D reconstruction and finally the obstacle detection.
3.4.8 Disparity Statistics for Pedestrian Detection: Combining Appearance, Motion and Stereo

**ID:** (WALK; SCHINDLER; SCHIELE, 2010) **Base:** Springer

**Detection Target:** Pedestrian.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.


**Comments:** Focusing on pedestrian detection, this work use different information to do this task, taking into account features from appearance, motion and stereo vision. Uses Histogram of Oriented Gradients (HOG) and Histograms of Flow (HOF) as characteristic descriptors. Also uses Support Vector Machines (SVM) and MPLBoost (which is an extension of Adaboost) as classifiers.
3.5 2011

3.5.1 Stereo-based Road Obstacle Detection and Tracking

**ID:** (NA; HAN; JEONG, 2011) **Base:** IEEE

**Detection Target:** Vehicles.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.


**Comments:** Focusing on vehicles detection, this work use Stereo Vision techniques. The matching cost calculator is based on Normalized Cross Correlation (NCC) aiming to improve the matching results. And they have an optimizer is based on Hierarchical belief propagation (HBP) global matching method. An image gradient (wich eight directions) is used to prevent the smoothing effect in the vehicles edges. The road profile is found by dominant line segment in V-Disparity through Hough transform. The position where vehicles and road surface have contact are found by intersections between line segments and road profile.
3.5.2 U-V-Disparity based Obstacle Detection with 3D Camera and Steerable Filter

**ID:** (GAO et al., 2011) **Base:** IEEE  
**Detection Target:** Obstacles in general.  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Comments:** Also based on Stereo Vision methods and in U-Disparity and V-Disparity data. They also have used the Hough transform to lines features extraction. Steerable filters are applied in U-V-histograms before the Hough transform to reduce noise. At last, they have extracted both road surface and road obstacles. They only presented the result with the disparity map and without the original image.
3.5.3 Event-Driven Track Management Method for Robust Multi-Vehicle Tracking

**ID:** (LIM et al., 2011) **Base:** IEEE  
**Detection Target:** Vehicles.  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Comments:** The stereo matching here is done by a Belief Propagation algorithm. Extract the road information with V-Disparity and then extract the
obstacles on the road. The vehicles classification from the obstacles detected occurs with the use of AdaBoost. A positioning estimate is given by a sub-pixel disparity of the target vehicle with the aid of strip-based disparity and calculates the overall position of the target by means of an Inverse Perspective Mapping (IPM) model. To associate multiple detections, a nearest neighbor scan is used for tracking using the extended Kalman filter.

Image:

Figure 33 – (LIM et al., 2011) results.

3.5.4 Stereo-Vision Based Free Space and Obstacle Detection with Structural and Traversability Analysis Using Probabilistic Volume Polar Grid Map

**ID:** (KANG; CHUNG, 2011)  **Base:** IEEE

**Detection Target:** Obstacles in general (Focus on finding free space for navigation).

**Handles shadows:** No.

**Identifies puddles:** No.  **Identifies potholes or damages:** No.

**Other features:** No.

**Methods:** Stereo Vision. Polar Grid Map. 3D reconstruction.
Comments: In this work they have as goal to finding the free space in front of the vehicles. To do this they have used Stereo Vision techniques and represent the scene as a Polar Grid Map based on disparity volumes.

Image:

![Image](image_url)

Figure 34 – (KANG; CHUNG, 2011) results.

3.5.5 Stereo obstacle detection in challenging environments: the VIAC experience

ID: (BROGGI et al., 2011)  
Base: IEEE  

Detection Target: Obstacles in general.  
Handles shadows: Yes (Nothing is said, but in the presented results the shadows are not considered as part of the obstacle).  
Identifies puddles: No.  
Identifies potholes or damages: No.  
Other features: No.  

Comments: One more work using Stereo Vision. Pre-processing with Bayer-patterned converts images to grayscale. Correction of lens distortion. Stereo pair rectification and uses a vertical Sobel filter. Disparity Map is computed by a Semi-Global method. A post-processing in the Disparity Map is performed, with smoothing and temporal filtering.
3.5.6 Vehicle Detection and Tracking with Affine Motion Segmentation in Stereo Video

**ID:** (MIYAMA; MATSUDA, 2011) **Base:** IEEE

**Detection Target:** Vehicles.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.

**Methods:** Stereo Vision. Disparity Map. Optical Flow.

**Comments:** With vehicle detection goal, this work uses Stereo Vision and Optical Flow to do this task. They also taking into account the road detection. according to the authors, the road detection with motion segmentation, as an affine parallax model on flat road, enables the detection of vehicles on road.

**Image:**

Figure 35 – (BROGGI et al., 2011) results.

**Image:**

Figure 36 – (MIYAMA; MATSUDA, 2011) results.
3.5.7 A Single Camera Based Rear Obstacle Detection System

**ID:** (YANKUN; HONG; WEYRICH, 2011)  
**Base:** IEEE  
**Detection Target:** Obstacles in general.  
**Handles shadows:** Yes.  
**Identifies puddles:** No.  
**Identifies potholes or damages:** No.  
**Other features:** Rear view.  


**Comments:** This work is aimed at rear view cameras, but it is kept in this review because it is within the criteria, after all the capture is with horizontally images and the position is the same if it were frontal (it is not a diagonal image for example). They start with distortion removal as pre-processing. Then a sum of frame difference is applied, similar a background subtraction and the difference image is transformed into a Inverse Perspective Mapping (IPM). Also a discontinuity-based segmentation is applied to found the objects edges.

**Image:**

![Image](image_url)  

Figure 37 – (YANKUN; HONG; WEYRICH, 2011) results.

3.5.8 Obstacle Detection Using Dynamic Particle-Based Occupancy Grids

**ID:** (DANESCU, 2011)  
**Base:** IEEE  
**Detection Target:** Obstacles in general.  
**Handles shadows:** No.  
**Identifies puddles:** No.  
**Identifies potholes or damages:** No.  
**Other features:** No.
Comments: Obstacle tracking with a Dynamic Particle-Based Occupancy Grids. They do the labeling of the grids. They map the 3D coordinates of the world from a bird’s eye view image into a representation of 2D grids. They also differentiate between static objects and moving objects.

Image:

Figure 38 – (DANESCU, 2011) results.
3.5.9 Obstacle Detection “for free” in the C-velocity space

**ID:** (BOUCHAFA; ZAVIDOVIQUE, 2011) **Base:** IEEE
**Detection Target:** Obstacles in general.
**Handles shadows:** No.
**Identifies puddles:** No. **Identifies potholes or damages:** No.
**Other features:** No.
**Methods:** Optical Flow. Hough transform histogram.
**Comments:** Uses the information obtained from movement, this movement being either the objects or the vehicle itself where the camera is to capture the images. For this it uses Optical Flow. It makes the location of the expansion focus, estimated by the velocity vectors of the Optical Flow. Also uses data from Histograms of the Hough transform.

**Image:**

![Figure 39 – (BOUCHAFA; ZAVIDOVIQUE, 2011) results.](image-url)
3.5.10 Fast Dynamic Object Extraction using Stereovision based on Occupancy Grid Maps and Optical Flow

**ID:** (SUGANUMA; KUBO, 2011) **Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** Yes (Nothing is said, but in the presented results the shadows are not considered as part of the obstacle).

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.


**Comments:** This work combines methods of Stereo Vision with the use of Disparity Maps that gives the notion of depth in the scene along with Optical Flow (by Kanade-Lucas-Tomasi) methods that pass the notion of movement of scene and objects. It also uses this information in an Occupancy Grid Map.

**Image:**

![Image](image-url)  
Figure 40 – (SUGANUMA; KUBO, 2011) results.
3.5.11 Dynamic obstacle identification based on global and local features for a driver assistance system

**ID:** (WOO; LIM; LEE, 2011) **Base:** Springer

**Detection Target:** Obstacles in general.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.

**Methods:** Modified GIST. MAX Pooling. Support Vector Machine (SVM). Dynamic Saliency Map.

**Comments:** This work uses combined Global and Local features. To the Global features extraction, the modified GIST descriptor with MAX Pooling orientation features is used. A Dynamic Saliency Map is used for localizing a moving obstacle area. Uses the Support Vector Machine (SVM) classifier. For the local features is used entropy maximization and also the SVM classifier.

![Image](image.png)

Figure 41 – (WOO; LIM; LEE, 2011) results.

3.5.12 New Single Camera Vehicle Detection Based on Gabor Features for Real Time Operation

**ID:** (BAIG et al., 2011) **Base:** Springer

**Detection Target:** Vehicles.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** Displays examples with vehicle detection inside a tunnel.


**Comments:** They make the Cross Correlation between two images looking
for similarities that allow to find regions where it probably has a vehicle, defining these regions as Regions of Interest (ROI). In this work Gabor filters are used to extract texture features (by Fourier transform). And they use information from the Gabor filters on the Support Vector Machine (SVM).

Image:

![Image](image.png)

Figure 42 – (BAIG et al., 2011) results.

3.5.13 Depth Calculation and Object Detection Using Stereo Vision with Subpixel Disparity and HOG Feature

**ID:** (SONG et al., 2011) **Base:** Springer

**Detection Target:** Pedestrian.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.

**Methods:** Region of Interest (ROI). Histogram of Oriented Gradient (HOG).

**Comments:** A Region of Interest (ROI) is defined using a Histogram of Oriented Gradient (HOG) descriptor with a Support Vector Machine (SVM) classifier. Stereo Vision and Disparity Map calculation are applied only in the Region of Interest (ROI). Uses the Harris corner detector in the Region of Interest (ROI) too.

**Image:**

Figure 43 – (SONG et al., 2011) results.

### 3.5.14 Integrated Real-Time Vision-Based Preceding Vehicle Detection in Urban Roads

**ID:** (CHONG et al., 2012) **Base:** Springer

**Detection Target:** Vehicles.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.
Other features: No.
Comments: This work focuses on vehicle detection. Use shadow information as a feature to locate vehicles defining a Region of Interest (ROI). After that they use Histogram equalization, Region of Interest entropy and mean of edges images (by Scharr Sobel and Roberts operators). It depends a lot on lighting conditions.

Image:

![Image](image-url)

Figure 44 – (CHONG et al., 2012) results.

3.5.15 Road environment modeling using robust perspective analysis and recursive Bayesian segmentation

ID: (NIETO; LABORDA; SALGADO, 2011) Base: Springer
Detection Target: Vehicles.
Handles shadows: Yes.
Identifies puddles: No. Identifies potholes or damages: No.
Other features: Displays examples with vehicle detection inside a tunnel.
Methods: Inverse Perspective Mapping (IPM). Vanishing Point detection. Recursive Bayesssian Segmentation. Expectation Maximization (EM). Kalman filter. Binarization. Opening morphological operation. Sobel. Histograms. Comments: Here they identify the area of the road, and then the vehicles in that area. In the first step the road area and the road markings are identified, using a Vanishing Point detection (with the help of Kalman Filter). In parallel, the Inverse Perspective Mapping (IPM) is applied and both enable Recursive Bayesssian Segmentation. Expectation Maximization (EM) is used to found the likelihood models. Vehicle detection is based on the segmented image. Through the binary image, a morphological opening operation to select only the vehicles is applied. Refining of the detection with Sobel edge detector and analysis of peaks in histograms.

Image:

Figure 45 – (NIETO; LABORDA; SALGADO, 2011) results.

3.5.16 Real Time Vision Based Multi-person Tracking for Mobile Robotics and Intelligent Vehicles

ID: (MITZEL et al., 2011) Base: Springer
Detection Target: Pedestrian.
Handles shadows: No.
Identifies puddles: No. Identifies potholes or damages: No.
Other features: No.
Comments: The goal of this work is to perform pedestrian detection. To do this they have used Stereo Vision techniques to do the odometry estimation and also the Histogram of Oriented Gradient (HOG) with the aid from an extended Kalman filter. Features extraction is performed by the Harris corner
detector. Followed by a Normalized Correlation. Finally, the motion estimation can be done by a RANSAC framework.

Image:

![Figure 46 – (MITZEL et al., 2011) results.](image)

3.6 2012

### 3.6.1 Monocular Vision-based Collision Avoidance System

**ID:** (HWANG; JI; KIM, 2012) **Base:** ACM  
**Detection Target:** Obstacles in general (Focus on finding free space for navigation).  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** Help for the visually impaired.  
**Methods:** Region of Interest (ROI). Background models. Labeling. Histograms. Binarization.  
**Comments:** This work have focus on finding free space for navigation and is not geared towards vehicles, being aimed at visually impaired people. But it is within the criteria of this review. The first step is to learn the background. A Region of Interest (ROI) is defined in the image to collect the points and estimate the backgrounds (5 frames in a row). The models contain combined values, hue and intensity. Obstacle detection occurs for each pixel. A pixel is classified as an obstacle if the hue histogram value and the intensity histogram are below a threshold. Next, a binary image is generated where pixels are labeled as “1” in regions with obstacles.
3.6.2 Road Environment Recognition Method in Complex Traffic Situations Based on Stereo Vision

**ID:** (CHEN; TSAI; LIN, 2012) **Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.


**Comments:** Stereo vision techniques are also used here. Matches between images are possible through the Semi-Global Blocking Matching method (SGBM), thus computing the Disparity Map with the depth information of the scene. Histogram of Oriented Gradient (HOG) is used to extract the obstacles features. Support Vector Machine (SVM) are used for classification. And this scheme is done within a Occupancy Grid structure.
3.6.3 Forward Obstacle Detection System by Stereo Vision

**ID:** (IWATA; SANEYOSHI, 2012)  **Base:** IEEE  
**Detection Target:** Obstacles in general.  
**Handles shadows:** No.  
**Identifies puddles:** No.  
**Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Stereo Vision. Dense Disparity Map. Smoothing filter. RANSAC.  
**Comments:** In this work Stereo Vision techniques are also used. Building Dense Disparity Maps. Smoothing filter is used to enhance the accuracy. They also detect the road surface and consider only the obstacles within that region. The road plan is obtained through RANSAC.
3.6.4 Obstacle detection using sparse stereovision and clustering techniques

**ID:** (KRAMM; BENSRHAIR, 2012) **Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.

**Methods:** Sparse Stereo Vision. V-Disparity histograms. DBSCAN algorithm.

**Comments:** This work uses sparse Stereo Vision. It uses V-Disparity histograms to identify relevant depths. And extracts, from a 3D map, successive sets of points that correspond to those depth values. A grouping step is applied to provide a location for the corresponding elements. These groupings are used to construct sets of obstacles. The clustering is done by the DBSCAN algorithm.

Figure 49 – (IWATA; SANEYOSHI, 2012) results.
3.6.5 Real-time obstacle detection based on stereo vision for automotive applications

**ID:** (ZHANG et al., 2012) **Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** Yes.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.

**Methods:** Stereo Vision. Disparity Map. Erosion and dilation morphological operations.

**Comments:** Stereo Vision and Disparity Map calculations are also used in this work aiming for depth information in the scene for the obstacles detection. At the end, to improve the results, morphological operations of erosion and dilation are applied to eliminate noise and fill small holes.
3.6.6 Vehicle Detection and Tracking using Mean Shift Segmentation on Semi-Dense Disparity Maps

**ID:** (LEFEBVRE; AMBELLOUIS, 2012) **Base:** IEEE
**Detection Target:** Vehicles.
**Handles shadows:** No.
**Identifies puddles:** No. **Identifies potholes or damages:** No.
**Other features:** No.
**Methods:** Stereo Vision. Disparity Map. Mean-Shift segmentation. Fuzzy sweep.
**Comments:** Also searching for depth information in the scene to detect obstacles, this work uses methods of Stereo View. Semi-Dense Disparity Maps are calculated. Unlike other works, in this the Disparity Map is calculated by a Fuzzy sweep, stereo and local. A Mean-Shift segmentation is used to extract each vehicle and track the points belonging to the same vehicle.

Figure 51 – (ZHANG et al., 2012) results.
3.6.7 Fast obstacle detection using targeted optical flow

**ID:** (BOROUJENI; ETEMAD; WHITEHEAD, 2012) **Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.

**Methods:** Optical Flow by LucasKanade (LK) and by Horn-Schunck (HS). K-means clustering.

**Comments:** This work uses the motion vectors of the obstacles obtained through Optical Flow. More specifically, targeted optical flow. At the end it makes grouping by K-means for the reconstruction of the detected obstacle. The Optical Flow is obtained by Lucas-Kanade (LK) and Horn-Schunck (HS).
3.6.8 Obstacle Detection and Classification in Dynamical Background

**ID:** (LIU; CUI; LI, 2012)  
**Base:** Science Direct  
**Detection Target:** Obstacles in general.  
**Handles shadows:** No.  
**Identifies puddles:** No.  
**Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Inverse Perspective Mapping (IPM). Homography. Fuzzy Neural Network. Vanishing Point detection.  
**Comments:** The obstacles detection is done in this work through an Inverse Perspective Mapping (IPM) and Homography. A Vanishing Point detection is applied to generate Inverse Perspective Mapping (IPM). The estimated homography of the road plane is used for image alignment. A classification of the objects through a Fuzzy Neural Network is performed. They present only one result.
3.6.9 Obstacle detection using stereo imaging to assist the navigation of visually impaired people

**ID:** (COSTA et al., 2012)  
**Base:** Science Direct

**Detection Target:** Obstacles in general.  
**Handles shadows:** No.  
**Identifies puddles:** No.  
**Identifies potholes or damages:** No.  
**Other features:** Help for the visually impaired.  

**Methods:** Stereo Vision. Disparity Map. Segmentation.  

**Comments:** This work aimed at visually impaired people. But it is within the criteria of this review. To perform the proposed task, Stereo Vision techniques are used. More specifically the calculation of the Disparity Map. In addition, a segmentation is done based on the Disparity Map. The object collision detection algorithm is based on disparity images. Empirical 2D Ensemble mode decomposition image optimization and two-layer disparity image segmentation are also performed to detect nearby objects. The computer...
vision module obtains disparity images and calculates the depth information required to perform layer image segmentation. Images are segmented at pre-defined distances to find nearby obstacles and to inform the user about how to avoid detected objects.

Image:

![Image](image.png)

Figure 55 – (COSTA et al., 2012) results.

3.6.10 Monocular Visual Odometry and Dense 3D Reconstruction for On-Road Vehicles

**ID:** (ZHU et al., 2012) **Base:** Springer  
**Detection Target:** Obstacles in general (Focus on finding free space for navigation).  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Disparity Map. KLT features tracker.  
**Comments:** This work focuses on finding free space for navigation. Unlike the vast majority of works, in this the disparity map is generated based on monocular capture. It depends on the movement in the scene. The features extraction is performed by the KLT method.
3.6.11 Symmetry-based monocular vehicle detection system

**ID:** (TEOH; BRÄUNL, 2012) **Base:** Springer

**Detection Target:** Vehicles.

**Handles shadows:** Partially.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.


**Comments:** Starts with border detection (with Canny edge detection) that helps to select the Region of Interest (ROI). The object selection box is based on the height and width of the object in the border image. Edge Oriented Histogram (EOH) is used before the images go to the classifier and serves to reduce the dimension of the classification. Support Vector Machine (SVM) is used as classifier. With the vehicle detected, a Kalman filter is used for tracking.
3.6.12 Subtraction-Based Forward Obstacle Detection Using Illumination Insensitive Feature for Driving-Support

**ID:** (KYUTOKU et al., 2012) **Base:** Springer  
**Detection Target:** Obstacles in general.  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Frames subtraction. Census transform. Hamming distance.  
**Comments:** This work depends on movement, because it is based on the subtraction of frames. It uses a dynamic deformation time method to obtain the correspondences between the frames. Census transform is also used to extract local features. Hamming distance is applied for the calculation of differences between frames.
3.6.13 Fast Stixel Computation for Fast Pedestrian Detection

**ID:** (BENENSON et al., 2012) **Base:** Springer  
**Detection Target:** Pedestrian.  
**Handles shadows:** No.  
**Identifies puddles:** No.  
**Identifies potholes or damages:** No.  
**Other features:** No.  
**Comments:** This work focuses on the pedestrians detection. To perform this task uses techniques that are based on Stereo Vision. It is proposed a world model called Stixel, which is composed of three parameters: ground plane, object distance and object height. The Stixels are obtained by analyzing disparities in V-Disparity and U-Disparity.
3.6.14 Pixels, Stixels, and Objects

**ID:** (PFEIFFER; ERBS; FRANKE, 2012) **Base:** Springer  
**Detection Target:** Obstacles in general.  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Stereo Vision. Stixel world. Kalman filter.  
**Comments:** This work based on Stereo Vision also uses the Stixel World model, where the perception of objects is represented vertically, while horizontal surfaces correspond to the ground. Also Kalman filter is used simultaneously in 3D position and 3D motion estimation. According to the authors, points features are extracted in a 6D Vision.
3.6.15 Mid-level Segmentation and Segment Tracking for Long-Range Stereo Analysis

**ID:** (HERMANN; BÖRNER; KLETTE, 2012) **Base:** Springer

**Detection Target:** Obstacles in general.

**Handles shadows:** Yes (Nothing is said, but in the presented results the shadows are not considered as part of the obstacle).

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.

**Methods:** Stereo Vision. Disparity Map. Optical Flow. Region growing segmentation.

**Comments:** In this work, Stereo Vision techniques are used to construct the Disparity Map that gives the depth information in the scene and about the obstacles contained in the scene. Optical Optical Flow detection is also used, allowing the movement analysis of participants in the scene. A segmentation is applied to the Disparity Map through a region growing segmentation algorithm.

**Image:**

![Image](image-url)

Figure 61 – (HERMANN; BÖRNER; KLETTE, 2012) results.

3.7 2013

3.7.1 Stereovision on Mobile Devices for Obstacle Detection in Low Speed Traffic Scenarios

**ID:** (TRIF; ONIGA; NEDEVSCHI, 2013) **Base:** IEEE

**Detection Target:** Vehicles.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.
Other features: No.
Comments: Vehicle detection is the focus of this work. After the input of the images stereo pair, the images are rectified. Then the Canny edge detector is used in the left image to reduce the correspondences search space. The left image is used as reference in the matches search and the Sum of Absolute Differences is used to identify the matches. Then the 3D reconstruction of the scene is made and the histogram of the depths are created. The detection of the vehicles occurs when there are points of great agglomeration in the depth histogram.

Image:

![Image](image_url)

Figure 62 – (TRIF; ONIGA; NEDEVSCHI, 2013) results.

3.7.2 Any Type of Obstacle Detection in Complex Environments based on Monocular Vision

ID: (LIU; YU; ZHENG, 2013) Base: IEEE
Detection Target: Obstacles in general.
Handles shadows: No.
Identifies puddles: No. Identifies potholes or damages: No.
Other features: No.
Comments: First, Forward-Backward error algorithm is applied in the original image for tracking the feature points. After that, using these points, the ground points are selected on top view images converted from the original images. Based on the road plan the parameters of vehicle movement can be estimated. Finally, by using the different movements between the obstacle and the road, noise and the obstacle region in the difference image based on motion compensation by Optical Flow are excluded.

Image:

Figure 63 – (LIU; YU; ZHENG, 2013) results.

3.7.3 Forward obstacle detection in a lane by stereo vision

ID: (IWATA; SANEYOSHI, 2013) Base: IEEE
Detection Target: Obstacles in general.
Handles shadows: No.
Identifies puddles: No. Identifies potholes or damages: No.
Other features: No.
Comments: This work is a continuation of (IWATA; SANEYOSHI, 2012). It also uses Stereo Vision techniques and depth information from the Disparity Map. The difference is that in this work they detect the road lane in which the vehicle is and detect the obstacles in that specific lane.
3.7.4 Stereovision for Obstacle Detection on Smart Mobile Devices: First Results

**ID:** (ONIGA; TRIF; NEDEVSCHI, 2013) **Base:** IEEE

**Detection Target:** Vehicles.  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Sparse Stereo Vision. Canny edge detection. 3D Triangulation.  
**Comments:** This work come before the (TRIF; ONIGA; NEDEVSCHI, 2013) work. Sparse Stereo Vision techniques are used in conjunction with Canny edges detection in the left image (similar to that presented in (TRIF; ONIGA; NEDEVSCHI, 2013)). Triangulation of the 3D points is also performed in the analysis of detected vehicles. The big difference here is not using the depth histogram.
3.7.5 Monocular Vision-Based Collision Avoidance System using Shadow Detection

**ID:** (ISMAIL et al., 2013) **Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.


**Comments:** In this work the shadows are considered features for the objects detection. Watershed Segmentation is used for the detection of obstacles and triangulation techniques to calculate distances. A Pre-processing step converts images to grayscale. The grayscale images are binarized applying a Thresholding to separate the background and the foreground with the shadow. Morphological erosion and dilation operations are also used to improve the
identification of the shadow region. After returning the image to grayscale the Watershed segmentation is applied.

**Image:**

![Figure 66 – (ISMAIL et al., 2013) results.](image)

3.7.6 Stereo vision-based road obstacles detection

**ID:** (KHALID; MOHAMED; ABDENBI, 2013) **Base:** IEEE  
**Detection Target:** Vehicles.  
**Handles shadows:** No.  
**Identifies puddles:** No.  
**Identifies potholes or damages:** No.  
**Other features:** No.  
**Comments:** Stereo Vision is used for the detection of scene depth and consequently obstacles detection. But they first detect the road region. A rectangular shape is used at the bottom of the image to bridge road disparities, such as a Region of Interest (ROI). The sides are extracted using the Hough transform. For the obstacles detection, a segmentation is made and the tracking is possible thanks to the Kalman filter. Analyzes based on disparity Histogram are also used.
3.7.7 A Novel Video Analysis Approach for Overtaking Vehicle Detection

**ID:** (CHANAWANGSA; CHEN, 2013) **Base:** IEEE

**Detection Target:** Vehicles.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** Overtaking situations.


**Comments:** The focus of this work is to detect vehicles in overtaking situations. To do this, firstly the lane markings detection is done, to identify the road lanes, this is possible by Vanishing points detection. Vehicles detection is possible by Hypothesis generation. The features extraction is done by Histogram of Oriented Gradients (HOG). And the Support Vector Machine classifier (SVM) is used. Vehicle tracking is possible through the Kalman filter.
3.8 2014

3.8.1 On-road multiple obstacles detection in dynamical background

**ID:** (LI; CHEN, 2014) **Base:** IEEE  
**Detection Target:** Obstacles in general.  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Comments:** They perform the Vanishing Point detection to identify the region where an obstacle could be, to do this task the road markings are extracted and combined with a temporal histogram-based segmentation. For the obstacle detection, Inverse Perspective Mapping (IPM) is used, which uses the vanishing point information with Homography estimation. The obstacles classification is possible through a Fuzzy Neural Network. The work also takes into account the geometric relationships to classify the objects. They present only a single result.
3.8.2 Obstacle Recognition for ADAS Using Stereovision and Snake Models

**ID:** (LIU; HUANG; ZHANG, 2014) **Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.

**Methods:** Stereo Vision. Dense Disparity Map. Snake models. Segmentation.

**Comments:** This work uses stereo Vision and consequently Dense Disparity Maps. Segmentations are applied in the Disparity Map in the XZ plane and also in the XY plane. An edge detection is also done, more specifically a contour extraction of objects, obtained by an improved Snake model. The height and width information of the identified objects are used to classify the obstacles.
3.8.3 Multiple Obstacle Detection and Tracking using Stereo Vision: Application and Analysis

**ID:** (WANG; FLOREZ; FRéMONT, 2014) **Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.


**Comments:** In this work Stereo Vision is also used to calculate the depth of the objects in the scene through the Disparity Map. The method is based on the use of Illuminant Invariant images to detect the free regions of the road. A Region of Interest (ROI) that includes the main road lane is obtained through a Convex Hull algorithm. Based on this Region of Interest, the U-Disparity
map is built to detect obstacles on the road. A modified particle filter is used for multiple obstacles tracking.

**Image:**

![Figure 71 – (WANG; FLOREZ; FRéMONT, 2014) results.](image)

### 3.8.4 UV disparity based obstacle detection and pedestrian classification in urban traffic scenarios

**ID:** (ILOIE; GIOSAN; NEDEVSCHI, 2014) **Base:** IEEE  
**Detection Target:** Pedestrian.  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Comments:** Stereo Vision is also used in this work. V-Disparity is used to calculate the road’s plane and U-Disparity to determine the obstacles. Extracts Regions of Interest (ROI) from the U and V Disparity results and uses Histogram of Oriented Gradients (HOG) to describe each pedestrian hypothesis. A Principal Component Analysis (PCA) is applied to the features for selection and projection in relevant spaces. Support Vector Machine (SVM) classifiers are trained taking into account relevant features in a large set with pedestrians and without pedestrians.
3.8.5 Two-Stage Obstacle Detection Based on Stereo Vision in Unstructured Environment

**ID:** (ZHANG et al., 2014)  
**Base:** IEEE  
**Detection Target:** Obstacles in general.  
**Handles shadows:** Yes.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Stereo Vision. Disparity Map. Saliency map. Improved Space-Variant Resolution (SVR).  
**Comments:** The depth of the scene is analyzed through Disparity Maps, made possible by Stereo Vision, in this work. An obstacle saliency map is extracted. And then the detection is refined to detect small obstacles through geometric relationships between 3D points using a improved Space-Variant Resolution (SVR).  

**Image:**

![Image](image-url)  
Figure 73 – (ZHANG et al., 2014) results.
3.8.6 Superpixel-based Obstacle Segmentation from Dense Stereo Urban Traffic Scenarios Using Intensity, Depth and Optical Flow Information

**ID:** (GIOSAN; NEDEVSCHI, 2014) **Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.

**Methods:** SLIC Superpixel segmentation. Stereo Vision. Optical Flow (Lucas-Kanade). Region of Interest (ROI).

**Comments:** This work uses several techniques for the obstacle detection task. Uses Stereo Vision for the notion of scene depth and to know the obstacles distance. Uses Optical Flow (by Lucas-Kanade) to identify obstacles movement. A Region of Interest (ROI) is defined excluding a small upper portion of the image. And also uses SLIC Superpixel segmentation for the scene labeling. At the end, intensity, depth and superpixel flow are integrated to segment the obstacles.

**Image:**

![Image](image-url)  

Figure 74 – (GIOSAN; NEDEVSCHI, 2014) results.
3.8.7 Obstacle detection using stereovision for Android-based mobile devices

**ID:** (PETROVAI et al., 2014) **Base:** IEEE
**Detection Target:** Obstacles in general.
**Handles shadows:** No.
**Identifies puddles:** No. **Identifies potholes or damages:** No.
**Other features:** No.
**Methods:** Stereo Vision. SLIC Superpixel segmentation. Region of Interest (ROI). Canny edge detection.
**Comments:** Stereo Vision along with SLIC Superpixel segmentation are used in this work. Firstly, the road and the road marks are detected and then selected the Region of Interest (ROI) where the probable obstacles are. A Canny edge detection is performed before stereo matching. The information obtained from 3D stereo reconstruction allows superpixels to be grouped into regions belonging to the same object.

**Image:**

![Figure 75 – (PETROVAI et al., 2014) results.](image)
3.8.8 Robust obstacle detection based on a novel disparity calculation method and G-disparity

**ID:** (WANG et al., 2014) **Base:** Science Direct  
**Detection Target:** Obstacles in general (Focus on finding free space for navigation).  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Comments:** This work aims to identify the free paths for navigation, and to do this uses Stereo Vision techniques. From the Disparity Map generated by the stereo pair the information of U-Disparity and V-Disparity are extracted. Line Segmentation is also performed. G-Disparity information (based on disparity gradient) is used to detect lateral planes. Obstacle detection occurs mainly in the U-Disparity.

**Image:**

Figure 76 – (WANG et al., 2014) results.
3.8.9 A motion detection model inspired by hippocampal function and its applications to obstacle detection

**ID:** (LIANG; MORIE, 2014) **Base:** Science Direct

**Detection Target:** Vehicles.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.

**Methods:** Neural Network. Edge detection. CA3-GU-CA1 (CGC) model.

**Comments:** The focus of this work is on motion detection for obstacle detection applications. Neural Network is used for this. It is proposed to use a model called CA3-GU-CA1 (CGC). This model uses edge detection images as the basis and detects the movement from these edges. The CGC model treats the extracted edges of the monocular image sequences and detects the movement of the edges on 2D segmented maps without image matching.

**Image:**

![Image](image-url)

*Figure 77 – (LIANG; MORIE, 2014) results.*
3.9 2015

3.9.1 Fast Stereo-based Pedestrian Detection using Hypotheses

**ID:** (KANG; LIM, 2015)  **Base:** ACM

**Detection Target:** Pedestrian.

**Handles shadows:** No.

**Identifies puddles:** No.  **Identifies potholes or damages:** No.

**Other features:** No.


**Comments:** A framework of multiple hypotheses is presented in this paper. Stereo Vision is used to calculate the Disparity Map. First estimate the road profile with V-Disparity, defining this region as a Region of Interest (ROI). Obstacles on the road are extracted together with the height of pedestrians in U-Disparity space. Then, the specific hypotheses of pedestrians are estimated by the information acquired from the disparity U and V. Several hypotheses corresponding to the same obstacle are merged. Third, the hypotheses are amplified by an adequate range for classification and pedestrians detection. Finally, the hypotheses verified are merged or discarded by a non-maximum suppression scheme (NMS).

**Image:**

Figure 78 – (KANG; LIM, 2015) results.
3.9.2 Perception in Disparity: An Efficient Navigation Framework for Autonomous Vehicles With Stereo Cameras

**ID:** (CAO; XIANG; LIU, 2015)  **Base:** IEEE

**Detection Target:** Obstacles in general (Focus on finding free space for navigation).

**Handles shadows:** No.

**Identifies puddles:** No.  **Identifies potholes or damages:** No.

**Other features:** With slope analysis.


**Comments:** This work aims to identify the free path for navigation in front of the vehicle. To do this, uses Stereo Vision techniques and calculates the Disparity Map of the scene, extracting information of depth and distance from the obstacles in relation to the vehicle. The great differential of this work is the use of the A* search algorithm to find a reasonable path in the disparity space. Uses V-Disparity data to find the road plan. It makes the road labeling in free spaces.

**Image:**

![Figure 79 – (CAO; XIANG; LIU, 2015) results.](image)

3.9.3 Forward stereo obstacle detection with Weighted Hough Transform and local temporal correlation

**ID:** (GUO et al., 2015)  **Base:** IEEE

**Detection Target:** Obstacles in general (Focus on finding free space for navigation).

**Handles shadows:** Partially.

**Identifies puddles:** No.  **Identifies potholes or damages:** No.
Other features: No.
Comments: This work makes obstacle detection and identifies the free path for navigation. The Weighted Hough transform is used for the obstacles detection. Techniques based on Stereo Vision are also used. The temporal correlation information from stereo is used. And a Histogram of Oriented Gradients (HOG) is used to extract linear relationship of the V-Disparity map.

Image:

![Image](image-url)

Figure 80 – (GUO et al., 2015) results.

3.9.4 Obstacle Detection Using Unsynchronized Multi-Camera Network

ID: (MHIRI et al., 2015) Base: IEEE
Detection Target: Obstacles in general.
Handles shadows: No.
Identifies puddles: No. Identifies potholes or damages: No.
**Other features:** No.


**Comments:** In this work the obstacles detection and also of the road surface detection are made. Both based on Stereo Vision. V-Disparity and U-Disparity images are used with a modified Hough transform on these images to find the road surface and obstacles. A Kalman filter is used for tracking.

![Figure 81 – (MHIRI et al., 2015) results.](image)

### 3.9.5 Fast Obstacle Detection Using U-Disparity Maps with Stereo Vision

**ID:** (ONIGA; SARKOZI; NEDEVSCHI, 2015) **Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.

**Methods:** Stereo Vision. U-Disparity. Threshold.

**Comments:** This work also uses Stereo Vision techniques for the obstacles detection task. In the first step the obstacles correspond to the peaks region in the U-Disparity map. These peaks are detected by a threshold. The following steps aim to refine the result. The second step iterates vertically by propagating the obstacle label to the neighboring pixels. Step three iterates horizontally.
Figure 82 – (ONIGA; SARKOZI; NEDEVŞCHI, 2015) results.

3.9.6 A clustering-based obstacle segmentation approach for urban environments

**ID:** (RIDEL; SHINZATO; WOLF, 2015) **Base:** IEEE
**Detection Target:** Obstacles in general.
**Handles shadows:** Yes.
**Identifies puddles:** No. **Identifies potholes or damages:** No.
**Other features:** No.
**Methods:** Stereo Vision. Disparity Map. Efficient Large-Scale Stereo Matching (ELAS).
**Comments:** Also with Stereo Vision, in this work a sparse set of points is selected according to local spatial condition and are grouped into neighborhood functions, disparity values and cost associated with the possibility of each point being part of an obstacle. Evaluated on the KITTI cases basis (GEIGER et al., 2013). They have used the Efficient Large-Scale Stereo Matching (ELAS) method for stereo matching.
3.9.7 Adaptive Saliency-weighted Obstacle Detection for the Visually Challenged

**ID:** (PODDAR; AHMED; PUHAN, 2015) **Base:** IEEE
**Detection Target:** Obstacles in general (Focus on finding free space for navigation).
**Handles shadows:** Partially.
**Identifies puddles:** No. **Identifies potholes or damages:** No.
**Other features:** No.
**Comments:** Once the input image is received, the Ulrich’s method is applied to obtain an initial mapping of the obstacles. The images are binarized based on a correspondence histogram and using the hue and value from the HSV color space. The Saliency Map is built using a spectral residual approach. Also uses a Gaussian filter in this step. Next, a saliency threshold based on adaptive histogram is applied. At the end the Otsu thresholding method is used to obtain the final results.
3.9.8 A Novel Stereovision Algorithm for Obstacles Detection Based on U-V-Disparity Approach

**ID:** (BENACER; HAMISSI; KHOUS, 2015) **Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.


**Comments:** Analysis in Disparity Maps obtained by Stereo Vision are done in this work. The information in the U-Disparity and V-Disparity spaces is analyzed. This gives insights into the road plan and likely obstacles. Matching is based on the Census transform.
3.9.9 Discrete-Continuous Clustering for Obstacle Detection Using Stereo Vision

**ID:** (BICHSEL; BORGES, 2015)  
**Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** No.

**Identifies puddles:** No.  **Identifies potholes or damages:** No.

**Other features:** No.

**Methods:** Stereo Vision. 3D Occupancy Grids. Bayesian approach. Digital Elevation Model (DEM). RANSAC.

**Comments:** In this work 3D occupation grids are built based on data obtained by Stereo Vision. As a first step the ground is estimated. Digital Elevation Model (DEM) is used for road surface representation with a RANSAC algorithm. Then the obstacles are grouped into a space of continuous and discreet representation. Finally, the confidence of each cluster is evaluated, eliminating objects of low probability. The spaces occupied in the grid are grouped and tracked over time. External points are filtered using a Bayesian approach.
3.9.10 A stereovision based approach for detecting and tracking lane and forward obstacles on mobile devices

**ID:** (PETROVAI; DANESCU; NEDEVSCHI, 2015) **Base:** IEEE  
**Detection Target:** Obstacles in general.  
**Handles shadows:** Partially.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Stereo Vision. Kalman filter. SLIC superpixel segmentation. Region of Interest (ROI). Canny edge detection.  
**Comments:** This work is a continuation from the previous work, (PETROVAI et al., 2014). With a step of road lane markings detection. It also uses Stereo Vision data. Obstacle detection is basically the same work, but with the use of Kalman filter in tracking.

**Image:**

![Figure 86](image1.png)  
Figure 86 – (BICHSEL; BORGES, 2015) results.

![Figure 87](image2.png)  
Figure 87 – (PETROVAI; DANESCU; NEDEVSCHI, 2015) results.
3.9.11 High-Performance Long Range Obstacle Detection Using Stereo Vision

**ID:** (PINGGERA; FRANKE; MESTER, 2015) **Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** Partially.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.

**Methods:** Stereo Vision. Local Geometric Criteria. Statistical Hypothesis.

**Comments:** In this work is used Stereo Vision, but without a Disparity Map calculating, that is, direct in the images, which according to the authors, improves the performance. It is also considered a Local Geometric Criteria. They also have applied statistical hypothesis tests.

**Image:**

Figure 88 – (PINGGERA; FRANKE; MESTER, 2015) results.
3.9.12 Driving space detection by combining V-disparity and C-velocity

**ID:** (DEGHDAHCE; BOUCHAFA, 2015) **Base:** IEEE  
**Detection Target:** Obstacles in general (Focus on finding free space for navigation).  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Stereo Vision. Disparity Map. V-Disparity. C-Velocity.  
**Comments:** This work has the goal of identifying free spaces for navigation. To do this it does analysis of depth and movement of the scene. To the depth, techniques of Stereo Vision are used, calculating the Disparity Map and consequently allowing to work with V-Disparity. For the motion, a motion approach model called C-velocity is used.

**Image:**

![Image](image.png)  
Figure 89 – (DEGHDAHCE; BOUCHAFA, 2015) results.

3.9.13 Rear obstacle detection system with fisheye stereo camera using HCT

**ID:** (KIM et al., 2015) **Base:** Science Direct  
**Detection Target:** Obstacles in general.  
**Handles shadows:** Partially.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** Rear view.  
**Methods:** Stereo Vision. Hierarchical Census Transform (HCT). Obstacle Candidate Region (OCR).  
**Comments:** This work is aimed at rear view cameras, but it is kept in this
review because it is within the criteria, after all the capture is with horizontally images and the position is the same if it were frontal (it is not a diagonal image for example). They use Fisheye stereo cameras and the data from the Stereo Vision capture. A Hierarchical Census Transform (HCT) is also applied to avoid lighting problems in stereo matching. This hierarchical approach aims to improve the computational efficiency. An Obstacle Candidate Region (OCR) is defined.

Image:

Figure 90 – (KIM et al., 2015) results.

3.9.14 Real-time obstacle detection with motion features using monocular vision

**ID:** (JIA; LIU; ZHU, 2015) **Base:** Springer  
**Detection Target:** Obstacles in general.  
**Handles shadows:** Yes.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** SIFT, SURF, Vanishing Point detection. Horizon line detection. Region of Interest (ROI).  
**Comments:** Find differences between obstacles and the road plan by means of two consecutive frames and movement features. They have applied a filter to refine results. A final process is performed to reduce false positives. Uses features points extraction like SIFT and SURF. They made vanishing point and horizon line detection to separate a Region of Interest (ROI), the bottom of the image.
3.10 2016

3.10.1 Robust and Low Complexity Obstacle Detection and Tracking

**ID:** (WU; ZHOU; SRIKANTHAN, 2016) **Base:** IEEE
**Detection Target:** Obstacles in general.
**Handles shadows:** Yes.
**Identifies puddles:** No. **Identifies potholes or damages:** No.
**Other features:** No.
**Comments:** This work makes use of data from the U-Disparity and V-Disparity spaces obtained from a Stereo Vision Disparity Map to perform the detection and tracking of objects. A Space of Interest (SOI) is defined and used to applied connected component labeling methods. This labeling helps to obstacles tracking in sequential frames by a color histogram for each obstacle, as a feature-based appearance model. The LAB color space is used to avoid illumination problems.
3.10.2 Dense Disparity Map-based Pedestrian Detection for Intelligent Vehicle

**ID:** (LEE; KIM, 2016) **Base:** IEEE

**Detection Target:** Pedestrian.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.


**Comments:** This work focuses on pedestrian detection. They use Stereo
Vision techniques and calculate the Disparity Map of the scene. Then the V-Disparity space is analyzed and an image binarization is performed. From this it is possible to extract road features. Height estimates and comparison are made to identify possible obstacle areas. Then a Bird’s Eye View Mapping is done and then a clustering. The area where the obstacles tend to be pedestrian is detected, and finally the pedestrian detection classification is made.

Image:

Figure 93 – (LEE; KIM, 2016) results.

3.10.3 Fast Obstacle Detection Using Sparse Edge-Based Disparity Maps

**ID:** (CARRILLO; SUTHERLAND, 2016) **Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.


**Comments:** This work is based on Sparse Stereo Vision. Performs edge detection based on disparity data. It then performs analysis based on U-Disparity and V-Disparity data. Allowing to estimate the ground plane and a segmentation with obstacle labeling only in the road region, ie as a Region of
Interest (ROI), Hough transform is used to estimate the road profile too. At the end, the Stixels are computed.

Image:

Figure 94 – (CARRILLO; SUTHERLAND, 2016) results.

3.10.4 Multi-class obstacle detection and classification using stereovision and improved active contour models

**ID:** (HUANG; LIU, 2016) **Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.

**Methods:** Stereo Vision. Disparity Map. Active Contour Models.

**Comments:** In addition to detection, this work classifies detected objects. It uses techniques of Stereo Vision and with that it can use Disparity Map data. Uses stereo information to segment background obstacles. Then apply an active contour model to extract the curved contours from the detected obstacles. Based on the extracted contour, geometric features, including proportion, area ratio and height, are integrated to classify object types: vehicles, pedestrians and others.
3.10.5 Off-road Path and Obstacle Detection using Monocular Camera

**ID:** (NADA V; KATZ, 2016) **Base:** IEEE  
**Detection Target:** Obstacles in general.  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Visual Odometry. FAST algorithm. Optical Flow.  
**Comments:** A 2D and 3D analyzes are done in this work. Visual odometry is used to convert 2D image sequences to 3D point clouds. Each frame has feature extraction with the FAST edge detector algorithm. It uses Optical Flow (Lucas-Kanade variation) in the extracted points.
3.10.6 Obstacle Detection in Stereo Sequences using Multiple Representations of the Disparity Map

**ID:** (BURLACU et al., 2016) **Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** Yes (Nothing is said, but in the presented results the shadows are not considered as part of the obstacle).

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.


**Comments:** This work can also be used as evaluation information by Stereo Vision. After calculating the Disparity Map, different representations of this depth map are applied, such as: U-Disparity, V-Disparity and $\theta$ Disparity. V-Disparity provides a ground plane estimation. U-Disparity is a column-wise representation of the disparity values. $\theta$ Disparity has the 3D scene information.

**Image:**

![Figure 97 – (BURLACU et al., 2016) results.](image)

3.10.7 Real-time rear obstacle detection using reliable disparity for driver assistance

**ID:** (YOO et al., 2016) **Base:** Science Direct

**Detection Target:** Obstacles in general.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** Rear view.

**Methods:** Stereo Vision. Disparity Map. SLIC Superpixel Segmentation. Pixel-wise gradients map. CIELAB color space.
**Comments:** The combination of different techniques are used in this work to do the obstacles detection. In the first step, in the features extraction, Disparity Maps obtained by Stereo Vision are used in conjunction with SLIC Superpixel segmentation, as well as Pixel-wise gradients map. The combination of these features is then made using the Voting Map of Obstacle Candidates. Finally, the resulting obstacle detection is performed. They worked in the CIELAB color space.

![Image](image1.png)

Figure 98 – (YOO et al., 2016) results.

### 3.10.8 Spatio-temporal analysis for obstacle detection in agricultural videos

**ID:** (CAMPOS; SOSSA; PAJARES, 2016) **Base:** Science Direct  
**Detection Target:** Obstacles in general.  
**Handles shadows:** No.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Spatio-Temporal Analysis. Segmentation. Opening morphological operation. CIELAB color space.  
**Comments:** In a first step, obstacles are detected using spatial information based on spectral color analysis and texture data. In a second step, temporal information is used to detect moving obstacles in the scene, which is of particular interest in elements camouflaged within the environment. They have worked in the CIELAB color space.

![Image](image2.png)

Figure 99 – (CAMPOS; SOSSA; PAJARES, 2016) results.
3.11 2017

3.11.1 Small obstacle detection using stereo vision for autonomous ground vehicle

**ID:** (GUPTA et al., 2017) **Base:** ACM  
**Detection Target:** Obstacles in general.  
**Handles shadows:** Yes.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** Focus on small obstacles that may appear on the road.  
**Comments:** Stereo Vision is used in this work. Pre-processing with Disparity Map by Semi Global Block Matching (SGBM) allowing a point cloud and depth variance. Then a combination of depth variation, depth curvature and image gradient information is made in a Markov Random Field framework to finally segment the obstacles. A semantic segmentation of the scene is done in parallel through Deep Learning to segment the path and help in the final filtering of the detected obstacles.

**Image:**

![Figure 100 – (GUPTA et al., 2017) results.](image)

3.11.2 Obstacle Detection in Outdoor Scenes based on Multi-Valued Stereo Disparity Maps

**ID:** (GE; LOBATON, 2017) **Base:** IEEE  
**Detection Target:** Obstacles in general.  
**Handles shadows:** Yes.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.

**Comments:** They have used Stereo Vision methods in this work. With a multiple disparity approach for each pixel. These multiple values are selected from a statistical analysis. At the end, obstacle detection occurs through an aggregate occupation map in the U-disparity space.

**Image:**

![Image](image_url)

Figure 101 – (GE; LOBATON, 2017) results.

### 3.11.3 A 2D/3D environment perception approach applied to sensor-based navigation of automated driving systems

**ID:** (LIMA; VICTORINO; NETO, 2017) **Base:** IEEE

**Detection Target:** Obstacles in general (Focus on finding free space for navigation).

**Handles shadows:** Yes.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** No.


**Comments:** Does a road region segmentation, with a pre-processing that used Gaussian filter, 3 different methods based on the original image are applied: a blue channel enhancement, lane marks information and hue channel from HSV. Then a linear segmentation based on these three images is applied, a weighted average of the intensities of the segmented images was performed. U-V Disparity Maps are obtained by Stereo Vision. At the end, 2D and 3D information is combined to identify the navigable path in an Occupancy Grid Map.
3.11.4 Accurate Vertical Road Profile Estimation Using v-Disparity Map and Dynamic Programming

**ID:** (PARK et al., 2017) **Base:** IEEE  
**Detection Target:** Obstacles in general.  
**Handles shadows:** Yes.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Methods:** Stereo Vision. Disparity Map. V-Disparity Map. Absolute Difference-Gradient (AD-GRAD).  
**Comments:** In this work Stereo Vision is used for the Disparity Map calculation. Absolute Difference-Gradient (AD-GRAD) is used for this. Based on this the V-Disparity map is generated. It seeks to identify the vertical road profile. At the end, as a refinement is made a detection of the end point of the ground, avoiding false positives at the top of the image.
3.11.5 Detecting Unexpected Obstacles for Self-Driving Cars: Fusing Deep Learning and Geometric Modeling

**ID:** (RAMOS et al., 2017) **Base:** IEEE  
**Detection Target:** Obstacles in general.  
**Handles shadows:** No.  
**Identifies puddles:** No.  
**Identifies potholes or damages:** No.  
**Other features:** Focus on small obstacles that may appear on the road.  
**Methods:** Deep Convolutional Neural Networks (CNN), Geometric Models, Labeling, Statistical Hypothesis, Stereo Vision, Stixels, Bayesian framework.  
**Comments:** This work applies Deep Learning and Geometric Models to detect small obstacles that may appear on the road. They use a variation of a Convolutional Neural Network to do a pixel labeling on: free space, road, obstacles, and background. Geometric models are applied through Stereo Vision inputs and Statistical Hypothesis tests. It uses a Bayesian structure to merge the semantic and stereo detections. Stixel is used to describe obstacles.
Figure 104 – (RAMOS et al., 2017) results.

3.11.6 Learning Framework for Robust Obstacle Detection, Recognition, and Tracking

**ID:** (NGUYEN et al., 2017) **Base:** IEEE  
**Detection Target:** Obstacles in general.  
**Handles shadows:** Partially.  
**Identifies puddles:** No. **Identifies potholes or damages:** No.  
**Other features:** No.  
**Comments:** Preprocessing is done with supervised and unsupervised training. K-means clustering and a Recursive Convolutional Neural Network (RCNN) are used. The first step is a generic detection of obstacles based on Stereo Vision and data from U-Disparity and V-Disparity. Then these obstacles are recognized as pedestrians or vehicles with the use of a Deep Learning model. And finally, these recognized obstacles are tracked.
3.11.7 Stixel Based Scene Understanding for Autonomous Vehicles

**ID:** (WIESZOK et al., 2017) **Base:** IEEE
**Detection Target:** Obstacles in general.
**Handles shadows:** Yes.
**Identifies puddles:** No. **Identifies potholes or damages:** No.
**Other features:** No.
**Comments:** Stereo Vision is used in this work. Stixel World is the result (perception of objects vertically, while horizontal surfaces correspond to the ground). The stixel height estimation is based on road color model information (by a 2D normalized histogram) and disparity (by V-Disparity). With the semantic segmentation allows the classification of objects in: (cars and pedestrians) or (vegetation and structures).
3.11.8 Obstacle Detection and Classification using Deep Learning for Tracking in High-Speed Autonomous Driving

**ID:** (PRABHAKAR et al., 2017) **Base:** IEEE

**Detection Target:** Obstacles in general.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** No.

**Other features:** Some results in rainy day.

**Methods:** Convolutional Neural Network (CNN). Support Vector Machine (SVM).

**Comments:** This work makes use of Deep Learning to do the obstacles detection task. A Convolutional Neural Network (CNN) is trained with the PASCAL VOC (EVERINGHAM et al., ) database. The experiments are evaluated in the KITTI (GEIGER et al., 2013) database. Support Vector Machine (SVM) is used for object classification.

**Image:**

![Image](image.png)

Figure 107 – (PRABHAKAR et al., 2017) results.

3.11.9 Negative Obstacle Detection for Wearable Assistive Devices for Visually Impaired

**ID:** (HERGHELEGIU; BURLACU; CARAIMAN, 2017) **Base:** IEEE

**Detection Target:** Negative obstacles.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** Yes.

**Other features:** Help for the visually impaired.
**Methods:** Stereo Vision. Disparity Map (by ELAS).

**Comments:** This work is aimed at helping the visually impaired. This work detects negative obstacles, such as potholes or low regions in relation to the ground plane. Stereo Vision techniques are used. A Disparity Map is constructed by the ELAS algorithm. The potholes are detected because they are black regions and cause failure in calculating disparity. Display results with large potholes near the camera.

**Image:**

![Image of potholes near the camera](image_url)

Figure 108 – (HERGHELEGIU; BURLACU; CARAIMAN, 2017) results.

### 3.11.10 Stereo Vision based Negative Obstacle Detection

**ID:** (KARUNASEKERA et al., 2017) **Base:** IEEE

**Detection Target:** Negative obstacles.

**Handles shadows:** No.

**Identifies puddles:** No. **Identifies potholes or damages:** Yes.

**Other features:** No.

Comments: This paper presents an approach to detect negative obstacles (e.g., potholes). But it has only one pothole result, a really large pothole with easy visual identification. Still, a good result. Stereo Vision techniques are used (Disparity Map). Extract the road profile through U-Disparity and remove the obvious obstacle points by identifying the peaks in the U-Disparity map. Then it uses this modified disparity map and generates the V-Disparity, which will be used to calculate the road area. Negative obstacles must be in the road region. Two Regions of Interest (ROI) are generated, one in the original rectified image and the other in the disparity map that corresponds to the road. All operations are performed on these two fragments. Through energy functions, possible regions of negative obstacles are located. A Superpixel segmentation help here. Disparity Map ROI is scanned line by line to find pixel fragments that correspond to disparity values that are less than the corresponding disparity value of the road for that line. Then these pixels are marked as possible negative obstacles. These marked pixels are checked with the U-Disparity map using the disparity value and the column if this pixel contributes a visible peak (using a boundary) on the U-Disparity map. The pixels filtered through two constraints will be marked as possible negative obstacles.

Image:

Figure 109 – (KARUNASEKERA et al., 2017) results.

3.11.11 3D visual perception for self-driving cars using a multi-camera system: Calibration, mapping, localization, and obstacle detection

ID: (HäNE et al., 2017) Base: Science Direct
Detection Target: Obstacles in general.
Handles shadows: No.
Identifies puddles: No. Identifies potholes or damages: No.
Other features: Multiple cameras around the vehicle. Focus on Simultaneous localization and mapping (SLAM).

Methods: Stereo Vision. Disparity Map. SURF. Occupancy Grid.

Comments: This work focuses on Simultaneous localization and mapping (SLAM). Multiple cameras are used around the vehicle, but for this revision the “frontal” images are considered, respecting the adopted criterion. A calibration is performed using the SURF algorithm to extract features and check corresponding points between images. Obstacle detection uses Stereo Vision and Disparity Maps. An Occupancy Grid is also used in the obstacle detection stage. Fisheye cameras are used in this work.

Image:

Figure 110 – (HäNE et al., 2017) results.
4 CONCLUSIONS

A priori, the work was categorized into three types of obstacle detection: “Vehicles”, “Pedestrians” or “Obstacles in General”. Being the first two to when the focus was only on one of these two detections and the last one when the work focused on any obstacle. However, during the analysis a new class was created (although it only contained two works), since they differed from all others. It was named “Negative Obstacles” (Figure 111). The works were also analyzed, verifying if they deal with shadows situations, if they identify puddles and potholes. The main methods used in each study were also checked.

Figure 111 – Detection Target Types. Obstacles in general (78). Vehicles (18). Pedestrian (12). Negative obstacles (2).

In most of the studies, Stereo Vision (SV) techniques were used to detect the obstacles, being 77 in all. The Disparity Map (DM) allows the scene depth analysis, allowing the identification of obstacles and their distance, and in most of these works the use of techniques based on the Disparity Map that allow to extract information from the road plan and separately from the obstacles, this is called V-Disparity and U-Disparity. This is possible by calculating disparity histograms in horizontal (V-Disparity) and vertical (U-Disparity) lines. Each plane in the world coordinate system will be shown as a line on the U-V Disparity Map, simplifying obstacle detection in a line detection (WANG et al., 2014; BENACER; HAMISSI; KHOUAS, 2015;
BURLACU et al., 2016; GAO et al., 2011; MHIRI et al., 2015; NA; HAN; JEONG, 2011).

Some studies have used, together with Stereo Vision techniques, Optical Flow methods to detect the movements and to track the obstacles in the scene (FRANKE et al., 2008; HERMANN; BÖRNER; KLETTE, 2012; KLAPPSTEIN et al., 2009; SUGANUMA; KUBO, 2011). Optical Flow detection is not restricted to use together with Stereo Vision techniques, the works of (LIU; YU; ZHENG, 2013) and (BOROUJENI; ETEMAD; WHITEHEAD, 2012), for example, have used object movement information independent of depth information.

The works categorized in the type: “Obstacles in general” could be divided into two types, those that identify obstacles regardless of what they are, searching only for a free path for navigation and those that classify obstacles, specifying the type, such as: vehicles, pedestrians, or others. For this classification the papers have used Support Vector Machines (SVM) (PRABHAKAR et al., 2017; CHEN; TSAI; LIN, 2012). Others works have used Fuzzy logic for the classification (LI; CHEN, 2014; LIU; CUI; LI, 2012).

A few works dealt with shadows situations, such as Jia, Liu e Zhu (2015) that makes Vanishing Point and Horizon Line detection to separate a Region of Interest, the lower part of the image. And uses feature point extraction with the SIFT method. The works of Zhang et al. (2012) and Zhang et al. (2014) also showed good results in situations with shadows, using Disparity Maps and morphological operations (erosion and dilation) in the images.

No work have presented problems with puddles. In relation to the potholes, two papers have presented results (HERGHELEGIU; BURLACU; CARAIMAN, 2017) and (KARUNASEKERA et al., 2017), focusing exclusively on the detection of negative obstacles (eg potholes), thus not fitting into other types of obstacles classifications. However, these works disregard other situations in the scenario as: shadows and detection of other obstacles. Yet they are excellent results and present a way and approach to dealing with these problems.


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ONIGA, F.; SARKOZI, E.; NEDEVSCHI, S. Fast obstacle detection using u-disparity maps with stereo vision. In: 2015 IEEE International


