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Real-Time Obstacle Detection Approach using Stereoscopic Images

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***Abstract* —** In this paper, we propose a new and simple approach to obstacle and free space detection in an indoor and outdoor environment in real-time using stereo vision as sensor. The real-time obstacle detection algorithm uses two dimensional disparity map to detect obstacles in the scene without constructing the ground plane. The proposed approach combines an accumulating and thresholding techniques to detect and cluster obstacle pixels into objects using a dense disparity map. The results from both analysis modules are combined to provide information of the free space. Experimental results are presented to show the effectiveness of the proposed method in real-time.

Index Terms — Obstacle detection, real-time, stereovision, disparity map.

1. Introduction

Obstacle detection is one of the fundamental problems of mobile robotics. In order to navigate in the world, it is necessary to detect those portions of the world that are dangerous or impossible to traverse. Popular sensors for range-based obstacle detection systems include ultrasonic sensors, laser rangefinders, radar, stereo vision, optical flow, and depth from focus. Because these sensors measure the distances from obstacles to the robot, they are inherently suited for the tasks of obstacle detection and obstacle avoidance. However, none of these sensors is perfect. Popular active sensors used for obstacle detection include laser, radar, lidar and ultrasonic sensors. The main advantage of active sensors is their ability to measure distance and speed of the target object in bad weather and poor lighting conditions. The major disadvantages of these sensors are interference with the environment, difficult interpretation of output signals, high power consumption, high acquisition price, poor resolution and incapability to detect small obstacles [1]. Moreover, stereo vision and optical flow are computationally expensive. Indeed, a motion based method uses the assumption that each moving object can be considered obstacle for this we need to compute a flow optic. The mainly problem of this method is located in computing and interpreting a flow optic in real times. Stereo vision systems have advantages of low cost, low power consumption, no interference with environment and a high degree of mechanical reliability. But the relatively slow processing speed of existing stereo vision methods limit their applications in real world problems, mainly due to the long computing time required for establishing stereo correspondences. However, visual navigation takes much attention after web cameras were introduced a few years ago since its cost is attractive comparing with previous sensors. Recent progress of processing techniques such as GPU and FPGA enables stereo reconstruction to run in real-time.

Stereo vision exploits the fact that a single point in a scene appears in slightly different locations in neighbouring views of the scene. If the views are from two suitably aligned and calibrated cameras, with parallel lines of sight, a feature in the left image is horizontally shifted relative to the feature in the right image. This image shift, called the disparity, is directly related to the distance from the camera to the point in the scene: distant points have small disparity, while nearby points have large disparity. A disparity map consists of all the possible disparity values in an image. This is an image of the same size as the stereo pair images containing the disparity for each pixel as an intensity value. Such a map is basically a representation of the depth of the perceived scene

In this paper, we propose a novel visual obstacle detection method which combines an accumulating and thresholding techniques to detect and cluster obstacle pixels into objects using a disparity map. The advantage of this approach is that it is very fast and permits us to detect a large number of obstacles of varied shapes and sizes.

This paper begins with an overview of the obstacle detection algorithms in the literature. Section 2 presents the proposed method: obstacles and free space detection from a dense disparity map. Experimental results are shown in section 3. Finally, we make concluding remarks.

2. Previous work

The perception of free space and obstacles in a scene is essential for safe driving. Among various sensors for scene perception, a stereo-vision is promising as it provides 3D perception data.

Numerous vision based works have tried to detect a specific object that is important in a traffic scene. The object includes pedestrian [2], vehicle [3], bicycle [4] and so on [5].

Obstacle detection through image processing has followed two main trends: single-camera based detection and two (or more) camera based detection (stereovision based detection). The monocular approach uses techniques such as object model fitting [6], appearance-based obstacle detection [1, 7, 8, 9] etc. The estimation of 3D characteristics is done after the detection stage, and it is usually performed through a combination of knowledge about the objects (color, texture) [10, 11] and the camera parameters.

The stereovision based approaches have focused on the binary classification problem of ground/obstacle separation. The methods are mainly categorized into three types: disparity map based, image remapping and 3D analysis method.

First, the disparity map based methods [12,13,14,15,16,17,18,19,20,21] detect obstacles on the basis of disparity calculations. They have the advantage of directly measuring the 3D coordinates of an image. The main constraints concerning stereovision applications are to minimize the calibration and stereo-matching errors in order to increase the measurement accuracy and to reduce the complexity (computationally expensive) of stereo correlation process. Second, the image remapping method utilizes an image transformation for ground/obstacle separation [22, 23, 24]. One common technique is called the IPM (Inverse Perspective Mapping) [24]. The IPM is a transformation between the ground plane and the image plane. By the IPM two virtual ground images are generated from original stereo images. With the flat ground plane assumption, any difference in the two ground images represents non-ground objects, i.e. obstacles. A similar principle is also applied to the work in [25], that a stereo matching with the original and the ground-compliant matching windows is used instead of the image transformation. The methods mentioned above do not need the full 3D reconstruction. However they have several limitations. Real urban areas often do not have lane marking, and roads are occluded by crowded traffic. The IPM method is sensitive to the error of the camera geometry with respect to the ground plane. In order to overcome the limitations mentioned above, some works have analyzed a 3D model of an environment. In [26], obstacles are detected by checking connectivity of points in the reconstructed point cloud. To reduce computational load and complexity of 3D analysis, the use of simplified models such as an elevation map [27, 28, 29] is popular.

Many obstacle detection methods have been proposed based on two approaches above, but the processing time and accuracy of the existing methods is not appropriate for real-time systems. Therefore, a new approach for obstacle detection based on disparity map is proposed in this paper. Our proposed method is faster and more accurate than existing methods for obstacle detection.

3. Proposed approach

This vision system has the task of detecting obstacles and recognizing safe navigable areas in an images pair. Using stereo reconstruction, a disparity image can be converted into set of 3-D points. The problem is now to identify the points among this set that belong to obstacle surfaces. For this, we propose a visual obstacle detection method which combines an accumulating and thresholding techniques to detect and cluster obstacle pixels into objects using a disparity map. The method for detecting obstacle points is presented in this section.

3.1 Obstacle detection method

3.1.1 Hypothesis

We assume that the ground is flat and appears on the disparity map as a contiguous zone of rows having the same disparity value. An object located on the floor (vehicle, pedestrian, tree) is characterized by a portion of vertical or quasi vertical plane in the scene. The objective is to find such plans from a stereoscopic view.

3.1.2 The Method

In this paper we propose a method for the detection of free space and generic obstacles in an indoor and outdoor environment, focusing on the analysis of the dense disparity map image. The idea of this approach is first to build the so-called new disparity map obtained by accumulating disparities along the lines of the disparity map image. This provides a side view of the scene being studied. Secondly this new-disparity map image is analyzed in order to extract the longitudinal profile of the scene in order to detect the ground and therefore to detect obstacles.

In the first time, for each row i of the disparity map image (LxC), the pixels which have the same disparity (d) are accumulated. See fig. 1.

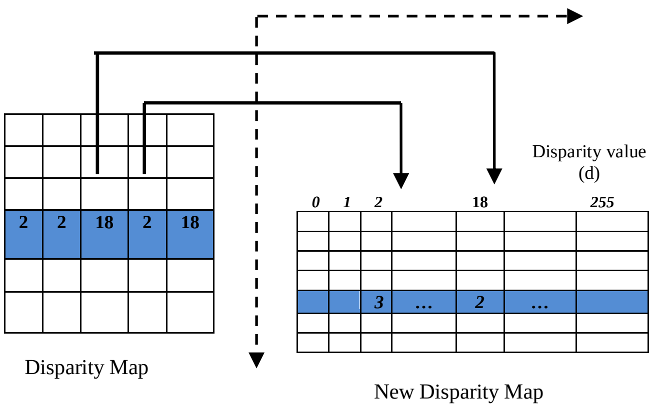


Figure. 1: New disparity map calculation

Then for each value of d, if the cumulative number corresponding to d is greater than some threshold S, the pixels which have a disparity equal to d in the row i are set to zero in the disparity image. Thus we obtain a map where dominant disparity is replaced by the value 0 which corresponds to the ground disparity.

In this way, we distinguish the pixels belonging to the ground plane characterized by the disparity value equal to 0 and those belonging to obstacles. Then the pixels belonging to obstacles are grouped according to criteria of connectivity in order to detect and separate all obstacles in the image disparity. Fig. 2 illustrates the obstacle detection process.

The value of the threshold S is important. Indeed, we remark, when we take a small value for the threshold S, we extract all the pixels belonging to the ground plane, but we obtain a less accuracy obstacle map. However, when we take a large value of the threshold S, we obtain more accuracy in the obstacle map, but it does not remove all the pixels belonging to the ground. So it is important to take a good value for this parameter for a good detection. Fig.3 shows the impact of the threshold value on the obstacle detection method.

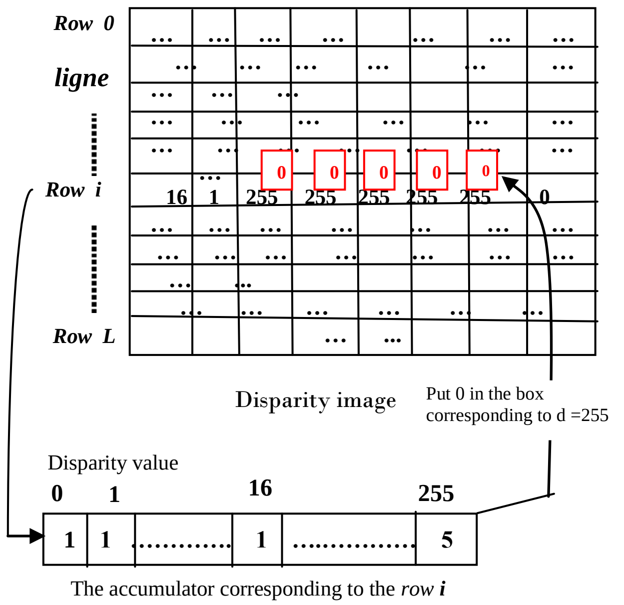


Figure.2: Obstacle detection process

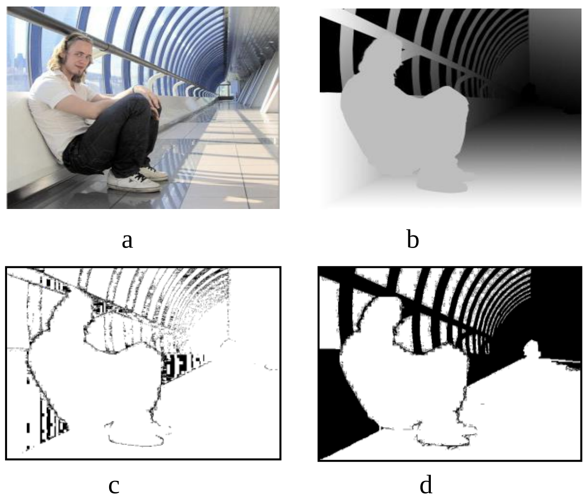


Figure. 3: a : original image, b : Disparity map, c : obstacle detection with small value of S, d : obstacle detection with a great value of S

The next algorithm shows a linear-time implementation of our obstacle detection method.

Input:

- Let D be the disparity map of L rows and C columns
- Let S be a threshold value.
- Let Accumulator be a vector of 256 cases corresponding to different disparity values.

Begin

For each row L **do**
  For each element $i \in$ Accumulatour **do**
    Accumulatour $[i] = 0$
  end for
    For each column $C \in$ row L **do**
    Accumulatour $(D(L, C))$++
  end for
  For j from 0 to 255 **do**
    If Accumulatour [j] >= S **then**
      For each column $k \in D$ **do**
        If $D(L, k) = j$ **then** $D(L, k) = 0$
        end if
      end for
  end if
  end for
end for
End

Output: obstacles map.

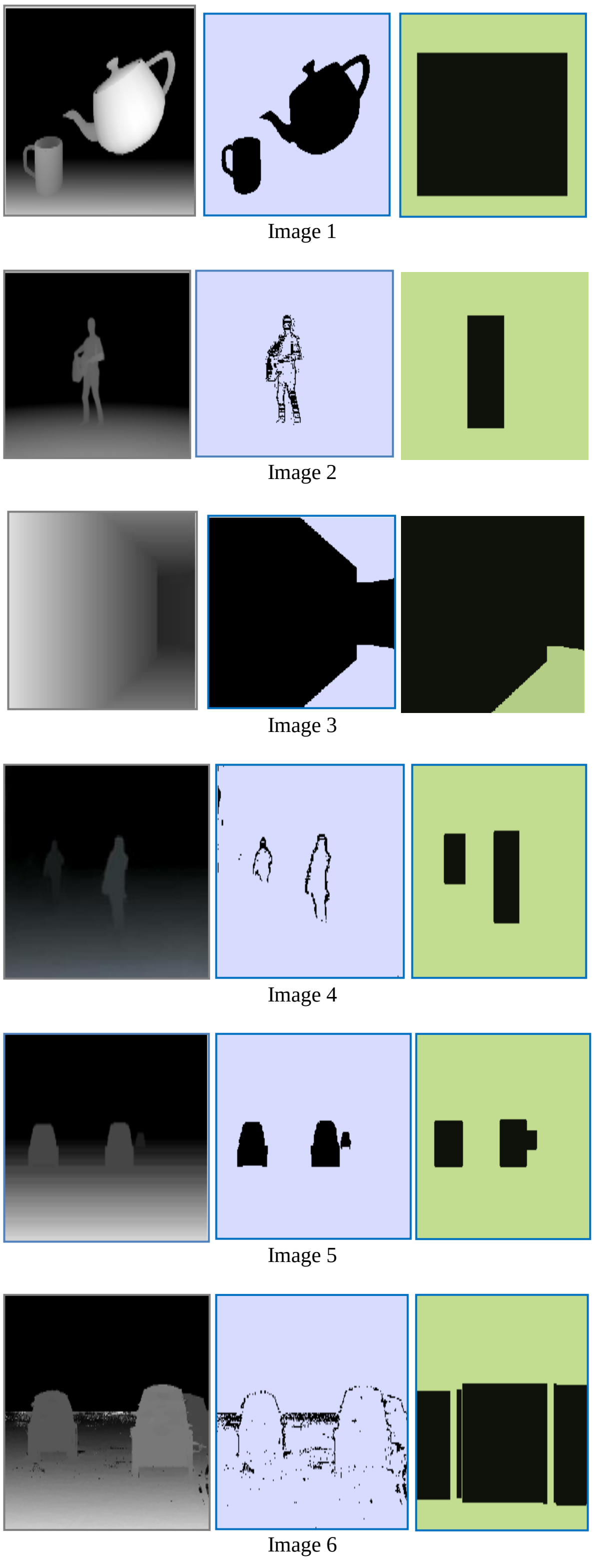
3.2 Free Space Computation

The obstacle detection algorithm described in the previous section generates an obstacle map where each obstacle can be described by the highest point on the left corner and the lower point on the right corner. Hence, bounding boxes are constructed around each obstacle, and then we obtain a free space estimation map which can be used by an autonomous mobile robot to allow a safe navigation.

4. Experimental results

In this section, we describe the experiments conducted to evaluate the performance of the proposed method. Our aim is to detect all obstacles in the scene and to obtain a fast runtime which is the requirement of any obstacles detection system of autonomous mobile robot navigation. To validate the proposed method described in the previous section, we tested it on several pairs of real images of different scenes collected from the websites [30, 31, 32, 33].

Fig. 4 shows the results obtained at each step of our obstacle detection approach. The first column shows the disparity maps corresponding to each image, second column shows the obstacle detection maps and the third column shows the free space maps obtained, where the obstacles are represented by black color and the free space is represented by the green color. Our method was tested on indoor and outdoor scenes.



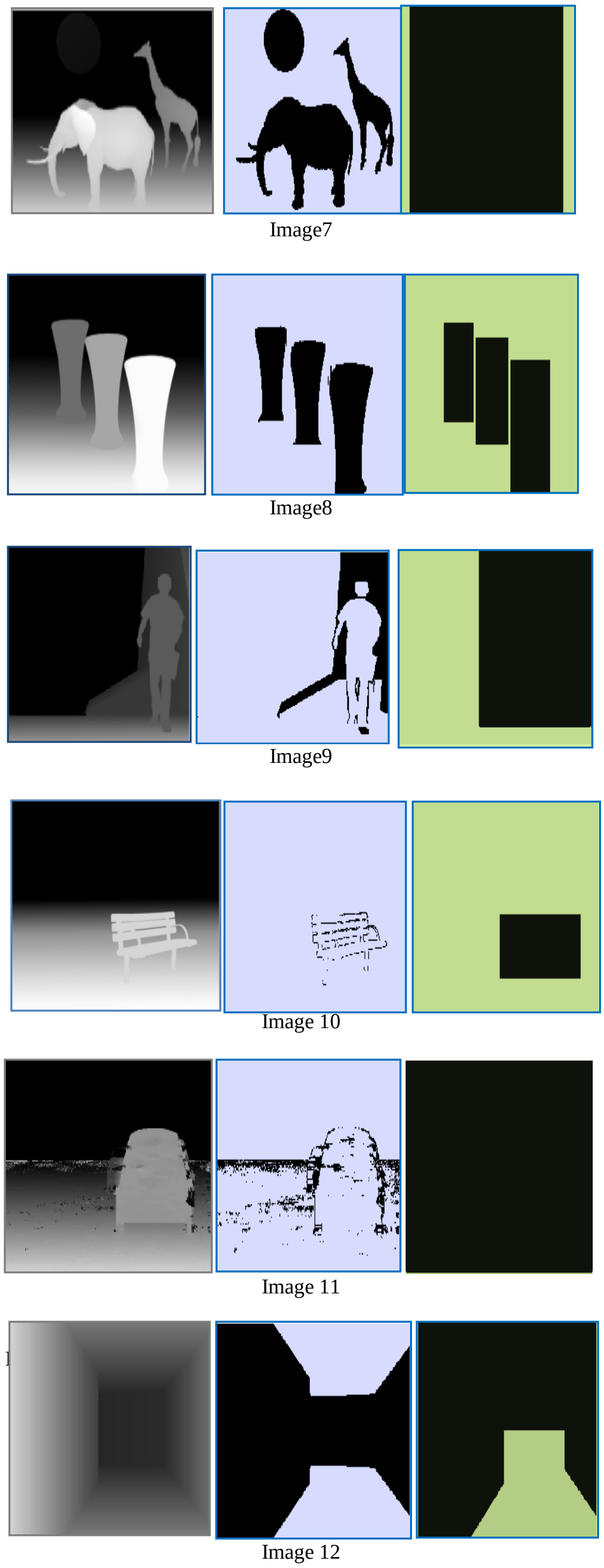


Figure. 4: Detection results in indoor and out door environment. First column: disparity image, second column: obstacle detection map , third column: free space map.

We note that in all images, the obstacles have been well detected, however when two obstacles are close, they are considered as one obstacle in the free space map. This is the case of the obstacles in image 1 and image 7 in Fig.4, the two respectively three obstacles are considered as a single obstacle in the free space map.

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Now we present a comparison between the proposed method and two methods described in the literature [16, 34].

An obstacle detection algorithm is not suitable for autonomous vehicle guidance if its computational demands do not allow for a sufficiently fast processing rate. Therefore, we computed the time needed to process stereo images pair by our approach. The proposed method was implemented using the C++ language and the timing tests were performed on a Personal computer PC, Dual-core T4500, 2.3 GHZ. We compared the performance of the proposed method to those of the other methods on the eleven images. Table 1 and Fig.5 illustrate the computation times obtained by our method in millisecond and two others methods [16] and [34]. For the other methods, we showed the computation time obtained on PC, Dual-core T4500, 2.3 GHZ. The proposed method yields favorable performances on all images, as compared to the other methods. The obtained results by our method showed that we are successfully able to detect obstacle in real-time. The total algorithm runs in less than 0,073ms. The fact that many parts of the algorithm can be processed in parallel, the calculation time can be reduced significantly if the algorithm is implemented using a parallel processing technique such as a GPU or FPGA devices.

5. Conclusion

This paper presented a new method for robust obstacle detection and free space map estimation using stereovision. The method makes use of thresholding and accumulating techniques to detect obstacles using a dense disparity map. The proposed method has been tested in various images, both in an indoor and outdoor environment. The processing times obtained for different images are less than 0,073 ms. In addition, the proposed method exhibited favorable performances as compared to two other methods. This makes our system suitable for real-time applications. Our system is expected to be used as a driving assistance system.

In future work, we plan to introduce in our method an image enhancement step to filter the input image with a 5×5 Gaussian filter to reduce the noise level. This eliminates the small variations between the neighboring pixels.

The performance might be improved, for example, by employing a parallel processing technique such as a GPU and FPGA devices.

References

[1] Mittal A., Sofat S. and Venkatesh M. A Novel Color Coherence Vector based Obstacle Detection Algorithm for Textured Environments. The 3rd International Conference on Machine Vision ICMV2010, 2010.

[2] Geronimo D., Lopez A. M., Sappa A.D., Graf T., Survey of Pedestrian Detection for Advanced Driver Assistance Systems, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 32, issue 7, 2010, 1239 - 1258.

[3] Sun Z., Bebis G., Miller R., On-road vehicle detection: a review, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 28, no. 5, May 2006, 694 - 711.

[4] Cho H., Rybski P.E, ZhangW., Vision-based bicycle detection and tracking using a deformable part model and an EKF algorithm, 2010 13th International IEEE Conference on Intelligent Transportation Systems (ITSC), 2010, 1875 - 1880.

[5] Kang J. ,Chung M.J Stereo-Vision Based Free Space and Obstacle Detection with Structural and Traversability analysis Using Probabilistic Volume Polar Grid Map, IEEE 5th International Conference on Robotics, Automation and Mechatronics (RAM) 2011.

[6] Nedevschi S., Schmidt R., Graf T.and Danescu R. High Accuracy Stereo Vision System for Far Distance obstacle Detection. IEEE Intelligent Vehicles Symposium, Parma, Italy, June 2004.

[7] Chan Nguyen Viet, An efficient obstacle detection algorithm using color and texture. World Academy of Science and Technology, 2009.

[8] Suard F. A Pedestrian detection using infrared images ad histograms of oriented gradients.Proceedings of the IEEE Intelligent Vehicles Symposium,Tokyo, Japan, june 2006.

[9] Ulrich I. , Nourbakhsh I.Appearance-Based Obstacle Detection with Monocular Color Vision. Proc. of the AAAI National Conference on Artificial Intelligence, Austin, TX, July/August 2000.

[10] Chumerin N., Ground plane estimation based on dense stereo disparity, Int. Conf. on neural networks and artificial intelligence,2008.

[11] Nguyen Viet C.,An efficient obstacle detection algorithm using color and texture, World Academy of Science and Technology, 2009.

[12] Nguyen T. Real-time obstacle detection for an Autonomous wheelchair using stereoscopic cameras" In Proc. Of the 29th Annual Inter. Conf. of the IEEE EMBS, August 2007, 4775-4778.

[13] Baha N., Larabi S. Obstacle Detection With Stereo Vision based on the homography.In proc. Acit 2013,2007, 65-71.

[14] Aldavert D. Obstacle Detection and alignment using an stereo camera pair. Technical report, Artificial Intelligence research institute, Spain, 2008.
[15] Chumerin N. Ground plane estimation based on dense stereo disparity. Int. Conf. on neural networks and artificial intelligence, 2008.
[16] Labayrade R, Aubert D. In vehicle obstacle detection and characterization by stereovision. In IEEE Intelligent Vehicles Symposium, Versailles.2004.
[17] Lorigo L.M, Brooks R.A. Grimson W.E.L, Visually guided obstacle avoidance in unstructured Environnement In IROS, 1997, 373-379.
[18] Burschka D., Hager G.Stage classification from dense disparity maps in indoor environments. In Proc of ICPR Quebec, August 2002.
[19] Zang Z., Weiss R., Hansoon A.R.Obstacle detection based one qualitative and Quantitative 3D reconstruction. IEEE Tran on pattern analysis and machine Intelligence, Janv 1997, 15-26.
[20] Okada R.,.Onouchi K. Obstacle detection using projective invariant and vanishing lines. IEEE Int Conf on Computer Vision France Octobre 2003.
[21] Aldavert D. Obstacle Detection and alignment using an stereo camera pairs pair. Technical report, Artificial Intelligence research institute, Spain, 2008.
[22] Kubota S., Nakano T., Okamoto Y. A Global Optimization Algorithm for Real-Time On-Board Stereo Obstacle Detection Systems. IEEE Intelligent Vehicles Symposium, 2007, 7 - 12.
[23] Xu Y., Zhao M., Wang X., Zhang Y., Peng Z., YuanY., Liu H. .A method of stereo obstacle detection based on image symmetrical move, 2009 IEEE Intelligent Vehicles Symposium, 2009, 36 - 41.
[24] Yang M., Yu Q., Wang H. Zhang B..Vision-based real-time obstacle detection and tracking for autonomous vehicle guidance. Proceedings Vol. 4666, Real-Time Imaging VI, February 2002, 65-74.
[25] Perrollaz M., Spalanzani A., and Aubert D.A probabilistic representation of the uncertainty of stereo-vision and its application to obstacle, IEEE Intelligent Vehicles Symposium (IV), June 2010, 313-318.
[26] Manduchi R., A. Castano A., Talukder A. and Matthies L.Obstacle and terrain classification for autonomous off-road navigation, Autonomous Robots, 2005, vol. 18, no. 1, 81-102.
[27] Vergauwen M., Pollefeys M., and Gool L. V.A stereo-vision system for support of planetary surface exploration, Machine Vision and Applications, April 2003, vol. 14, no. 1. 5-14.
[28] Kayama K., Yairi I.E., Igi S..Construction of elevation map for usercarried outdoor mobile robot using stereo vision, IEEE International Conference on Systems, Man and Cybernetics, 2003, 4631 - 4636.
[29] Oniga F., Nedevschi S..Processing Dense Stereo Data Using Elevation Maps: Road Surface, Traffic Isle, and Obstacle Detection," IEEE Transactions on Vehicular Technology, March 2010, vol. 59, issue 3, 1172 - 1182.
[30] http://www.cl.cam.ac.uk/research/rainbow/projects/dcbgrid/datasets/
[31] http://www.computerbase.de/forum/showthread.php?t=677436&page=3
[32] http://www.indasoftware.com/ru/stereo/depthmaps.php
[33] http://www.google.com/search?q=carte+de+profondeur&hl=en&prmd=imvns&source=lnms&tbm=isch&ei=CebQT5W0DpCM4gT7kezRDA&sa=X&oi=mode_link&ct=mode&cd=2&ved=0CEIQ_AUoAQ&biw=1280&bih=705.
[34] Lefebvre S. Mise en correspondance stéréoscopique de fenetres monodimenensionnelles par logique floue: application à la détection d'obstacles routiers. Thesis in INRETS-LEOST, France, July 2008.

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TABLE 1: Processing time obtained by different methods

Processing time (ms)	Image1	Image2	Image3	Image4	Image5	Image6	Image7	Image8	Image9	Image10	Image11
Ours	0,047	0,041	0,016	0,041	0,047	0,031	0,032	0,057	0,015	0,031	0,073
[34]	0,608	0,764	1,03	0,671	0,719	0,795	0,406	0,631	0,25	0,733	0,78
[16]	16,157	16,063	15,093	16,047	15,125	15,155	16,11	15,051	16,015	16,047	16,157

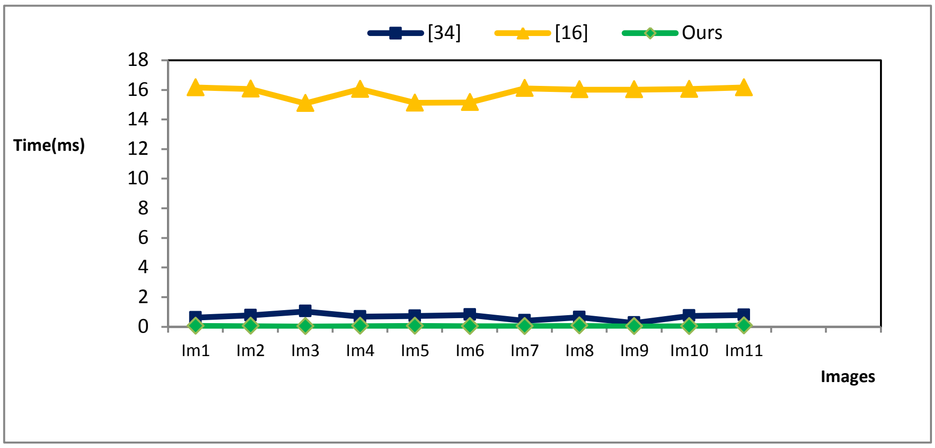

Figure 5: Processing time obtained by different methods

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