Robust Lane Extraction Using Two-Dimension Declivity

Mohamed Fakhfakh[1,2(✉)], Nizar Fakhfakh[2], and Lotfi Chaari[1,3]

[1] University of Sfax, Sfax, Tunisia
mohamed.fakhfakh.research@gmail.com
[2] NAVYA, Paris, France
nizar.fakhfakh@navya.tech
[3] IRIT-ENSEEIHT, University of Toulouse, Toulouse, France
lotfi.chaari@enseeiht.fr

Abstract. A new robust lane marking extraction algorithm for monocular vision is proposed based on Two-Dimension Declivity. It is designed for the urban roads with difficult conditions (shadow, high brightness, etc.). In this paper, we propose a locating system which, from an embedded camera, allows lateral positioning of a vehicle by detecting road markings. The primary contribution of the paper is that it supplies a robust method made up of six steps: *(i)* Image Pre-processing, *(ii)* Enhanced Declivity Operator (DE), *(iii)* Mathematical Morphology, *(iv)* Labeling, *(v)* Hough Transform and *(vi)* Line Segment Clustering. The experimental results have shown the high performance of our algorithm in various road scenes. This validation stage has been done with a sequence of simulated images. Results are very promising: more than 90% of marking lines are extracted for less than 12% of false alarm.

Keywords: Curve lane detection · Declivity operator
Road marking · Clustering · Hough transform

1 Introduction

Since the last decade, autonomous driving has become a reality due to algorithmic and computational advancements. According to the Society of Automotive Engineers, different levels of driving automation are defined. The highest level consists of a "full-time performance by an automated driving system of all aspects of the dynamic driving task under all roadway and environmental conditions that can be managed by a human driver". This high level of automation requires well-designed algorithms with high performances to deal with all of challenging use cases usually encountered in real-world. Algorithms must be real-time, accurate, reliable and robust to achieve a dynamic secure driving.

Such a vehicle is equipped with a set of active and passive sensors to perform functions, inter alia, obstacles detection and tracking [1,2] objects recognition [3], free space detection [4], global and local vehicle guidance [5]. During the

L. Rutkowski et al. (Eds.): ICAISC 2018, LNAI 10842, pp. 14–24, 2018.
https://doi.org/10.1007/978-3-319-91262-2_2

last decade, many researchers have proposed solutions for lateral positioning by embedded cameras.

In order to perform global vehicle positioning, several algorithms were designed by using advanced technologies, such as lidars [6] and differential GPS [7]. These solutions cannot respond to all of contexts and are mainly dependent on the environment. However, a lidar-based perception of loosely structured scenes could not give accurate global localization and can potentially fail in certain cases. In contrast, by using GPS technology, the localization is inaccurate because of the multipath problem in dense and highly structured scenes. In recent years, Visual SLAM algorithms [8] have been proposed as an alternative to improve the localization task and to deal with drawbacks of lidar and GPS technologies. Nevertheless, Visual SLAM-based algorithms remain insufficient and suffer from limits related to the processing time and the difficulty to accurately detect landmarks in challenging environments.

In this context, the present work is dedicated to Road Marking Extraction by mono camera in complex environments. Such an algorithm is usually used to perform path planning, lane departure warning or lane changing functions.

This paper is organized as follows: after an introduction covering the context of this research and the problem to be handled, Sect. 2 is dedicated for a state of the art from which our research is based. In Sect. 3, an overview of the proposed algorithm is presented and all of steps are detailed for road marking extraction in challenging environment by embedded camera for lateral positioning. Evaluation and experimental results are detailed in Sect. 4, and we finish by a discussion about the different axes to go further.

2 State of the Art of Road Marking Approaches

By referring to the literature, one of the first approaches for road marking detection is to apply a simple Hough Transform on the image in order to detect straight lines. This step is usually performed either on original images obtained with the projective model [9] or after applying an inverse perspective transform [10] which reflects the real geometry of lanes, but may introduce a loss of data because of the transformation step.

The most common way to address this task is to apply a thresholding step on the input image to extract pixels having intensities higher than a given threshold which typically correspond to road markings. Clearly, this is only true in the special case of a dark road and bright markings, which is not the case in the presence of partial shadows or high local variation of intensities.

There exist different methods of thresholding. It is commonly applied by using the histogram of gray levels and allows correctly separating the foreground from the background if the histogram clearly contains distinct peaks. Either global and local thresholding procedures can be considered [11,12].

In [13], the Otsu method requires the calculation of a gray level histogram before estimating an overall threshold. The idea of the OTSU algorithm is to divide the image histogram into two classes of pixels, the foreground and the background. The optimal threshold is calculated to separate the two classes so that their intra-class variances are minimal. However, the main limitation is the High brightness or shadows in the image, where the result of the road features extraction is not satisfactory.

The standard Otsu algorithm is affected by the presence of shadows or high brightness. Scholars X. Jia from Jilin University developed the optimized Otsu method based on the maximal variance threshold in order to solve the problems posed by the standard Otsu method [13]. The general idea of "optimized Otsu" consists of cutting the region of the road into several rectangular regions and treating each sub-region respectively according to the Otsu method. Then apply the maximum variance threshold segmentation method to process the contrast sequence. This family of approaches present the disadvantage of having a fairly large processing time.

Tang [14] proposed a method based on progressive threshold segmentation. The objective of considering each line of the image as a unit of image is to considerably reduce the impact of the contrast, light or shadow changes. The distribution of the gray levels of each image line follows a certain distribution and generally presents two peaks: a large peak corresponding to the background or the road, and a second peak corresponding to the markings. The threshold taken is the one that separates these two distributions. To reduce the computational time, the upper region of the image defined as being beyond the horizon line is set to zero.

In [15,16], the contrast in the image is automatically adjusted for each image. Adaptive thresholding was used for each pixel to improve the primitive extraction and binarization step.

Contrary to the first approach, a classification of the primitives was carried out on a bird's eye view. This view is obtained by a geometric transformation of the basic image to another projective plane, using the intrinsic parameters of the camera and the Homography matrix, this is an Inverse Reverse Transformation (IRT). Thereafter, an image segmentation process is applied whose purpose is to have a robust marking extraction. The procedure consists mainly of a filtering step with the Gaussian filter, and an adaptive thresholding method.

Based on a thorough reading of the various methods of binarization, we noticed some limitations due to the low or high brightness in the image:

- Images with presence of shadows: no method is able to extract the line marking in these types of complex images. Some markings are not extracted because the gray level values associated with the pixels are often below the threshold.
- Bright images: most methods of extracting the road markings give poor results with this type of images. Usually, there is a difficulty in identifying and extracting markings. In this case, the distinguishing between the regions corresponds to the line markings remains a difficult operation since the gray level values of the pixels corresponding to the markings and those of the road are almost the same.

3 Strategy for Lane Marking Extraction

We present here our approach which has been designed to cope with the limitations of previous methods of the literature. Figure 1 shows the flow diagram of lane extraction.

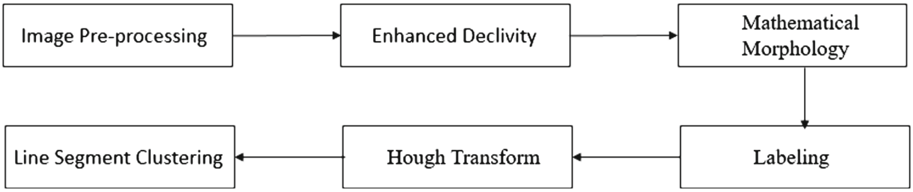


Fig. 1. The structure of our algorithm.

3.1 Image Preprocessing

This step consists of preparing the images by filtering them in order to reduce the noise caused by the acquisition process or by the impact of the illumination conditions of the environment. We chose to apply a Gaussian filter with a 1D kernel. This choice is justified by the fact that we are estimating a threshold for each image line by applying an improved gradient approach described in the following paragraph.

3.2 Enhanced Declivity

The declivity [17,18] has been proposed for contour detection. It is of the same family as the Canny and Deriche methods [19] which propose an optimal filter for contour detection. The response of these filters largely depends on their setting. Indeed, it is necessary to fix in advance the size of the filter for the Canny algorithm and a Deriche scale setting parameter. In order to produce satisfactory results on all types of images, the estimation of optimal values is still a challenging problem.

A declivity is applied on an image line whose gray levels are represented according to their position. The declivity makes it possible to identify the increasing and decreasing peaks, and is characterized by the following parameters:

- The bounds: x_i and x_j.
- The direction of the declivity: increasing "e" if $\mathrm{I}(x_i) < \mathrm{I}(x_j)$ or decreasing "d" otherwise.
- The width "l": $x_j - x_i$.

Figure 2 summarizes the concept of declivity. From the short gray levels per line, the objective is to identify ascendants and descents that have a high probability to correspond to the marking. We propose a new criterion which consists

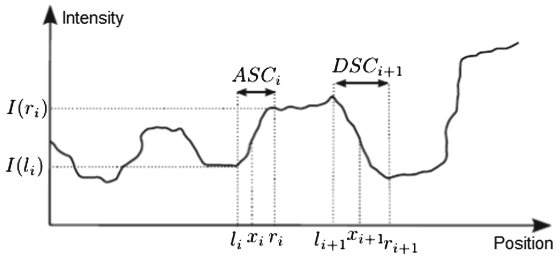


Fig. 2. Principle of the declivity.

of matching the ascending slopes with the descending slopes. We also propose a new thresholding by line which is defined as the average of the height of the ascendant declivity. The width of a slope has been defined differently from the basic version: the width "l" corresponds to the width of the cut of a ascending slope and a descending one at height α h. Note D the set of declivities and N the total number of declivity per image line. The threshold of the line j, denoted S_j is given by the following criterion:

$$S_j = \sum_{i=1}^{N} D_i(h, c), \tag{1}$$

where $D_i(h, c)$ corresponds to the height of the rising i.

To merge declivities, we apply the following algorithm: for each declivity upward slope, we seek for the most appropriate descending slope in an interval defined for each line. This interval is related to the possible width of a marking in the image. A correspondence table is created from the width in pixel of the nearest marking (the lowest in the image). This procedure will assign an ascendant peak to a descendant one. It is thus possible to identify a potential marking segment. Figure 3 shows the gray levels of a real image line, the ascendant and descendant peaks.

A declivity is valid if each ascending slope (in red) corresponds to a valid descending slop (in blue) in a given interval, and if the height of the declivity is

Fig. 3. Example of a valid declivity on an image line. (Color figure online)

greater than a threshold S_j. The algorithm of the improved declivity is summarized in Algorithm 1.

Algorithm 1. *E*xtraction algorithm.

1. Preprocessing: Application of a 1D Gaussian filter
2. For each line j do
  2.1 Compute the declivity on the appearance of gray levels
  2.2 Association of ascending and descending declivities
  2.3 Compute a threshold per line: $S_j = \sum_{i=1}^{N} D_i(h, c)$
  2.4 For each declivity D_i
    2.4.1 If $D_i(x_j) < S_j$ and $l < l_s$; l_s : is interval limit
      Retain the pair of declivities.
      Consider the width of the valid associated declivities as the width of the marking.

The Association step allows regrouping each main ascending declivity MAD with the next main descending declivity MDD. A MAD could correspond to the left side of a road marking and a MDD probably correspond to the right side of the same road marking. It could exist some local variation between a MAD and a MDD which might correspond to a shadow or other noise. These artifacts are represented as small, negligible, and insignificant declivities and consequently removed to consider only relevant declivities.

The previous algorithm is designed to highlight all of possibles road marking segments per image line from which are based the next steps of extraction.

The obtained result is a binary image with segments which the left side for each corresponds to the beginning of a road marking, and the right side is the end.

3.3 Morphology Filtering

This step consists of applying a mathematical morphology operation on theenerated binary image. This image contains the center of each segment detected with the Enhanced Declivity algorithm. We found that the result of this first phase of detection highlights the true marking which has the particularity of being compact, dense and continuous while the distribution of noise, or false detections, is rather random. We chose to apply a dilatation in order to connect the segments and keep this continuity between segments.

3.4 Labeling

The labeling consists of defining primitives by grouping the related pixels. A pixel is added to a component if there are neighboring pixels in the previous row and/or column belonging to the same component. Once the image is labeled, a primitive is defined for each object in order to detect and characterize all the objects in the image: the surface, the bounding box (*Umin, Umax, Vmin, Vmax*).

Primitives with a surface area below a certain threshold are not taken into account in the detection phase. Only the most significant primitives are detected. This filter allows us to avoid accounting for small objects and large objects that do not correspond to the channels, as well as reducing the background noise. Figure 4 below shows the result of the morphological filtering on the obtained binary image and the image after thresholding.

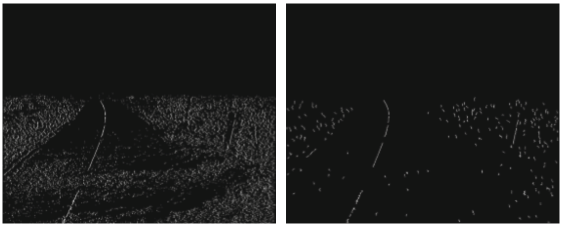
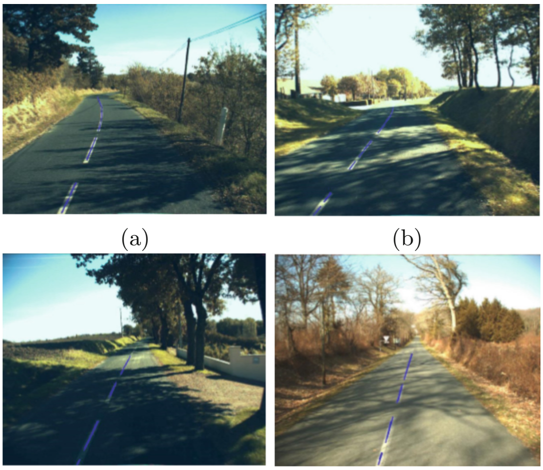


Fig. 4. Left: Dilatation. Right: After thresholding.

The morphological operation allows connecting neighboring pixels within small local regions in order to highlight the true road markings. The filtering step allows removing all small and isolated clusters of pixels.

3.5 Line Detection and Segments Grouping (Clustering)

On the obtained image, we apply the Hough transform [20,21] for the detection of straight lines. We get a set of segments that will be grouped into different



(a) (b) (c) (d)

Fig. 5. Some results on a complicated image set.

classes from a clustering algorithm [22] that we have developed. Two segments are classified in the same class if they respect the alignment and orientation constraints. Figure 5 shows the result of our different algorithms on certain images considered very complicated in the state of the art.

4 Experimental Results

The proposed method is tested on different conditions of road marking (simple and complex real conditions). The results of our experiment indicate the good performance of our algorithm for lane detection, especially under some challenging scenarios.

4.1 Quantitative Evaluation

The lane marking detection algorithm described in this paper has been implemented on a computer that had an Intel i7, 2.40 GHz CPU. The algorithm was executed in Visual C++ with OpenCV. The processing time was approximately 25 ms. per frame in good and complex road condition. As part of the evaluation of our approach, we have images from the "ROMA" database. It comprises more than 100 Heterogeneous images of various road scenes. Each image is delivered with a manually constructed ground truth, which indicates the position of the visible road markings.

Table 1. Quantitative performance of our algorithm.

Progressive threshold			Optimized Otsu			Our approach		
TDR	TPR	FPR	TDR	TPR	FPR	TDR	TPR	FPR
67.42%	32.55%	20.22%	80.63%	20.11%	51.39%	91.72%	7.26%	11.98%

Table 1 shows the performance of our method in terms of the algorithm. Figure 6 show the final results of our algorithm. TDR denotes the successful points marking detection rate while, TPR is the True Positive Rate, and FPR is the False Positive Rate.

$$TDR = \frac{\text{the number of successful lane markings}}{\text{the number of white points in ground truth}} \tag{2}$$

$$FPR = \frac{\text{the number of points markings detected but not exist in ground truth}}{\text{the number of white points in ground truth}} \tag{3}$$

$$TPR = \frac{\text{the number of points markings exist in ground truth but not detected}}{\text{the number of white points in ground truth}} \tag{4}$$

Our extraction approach has been evaluated and compared with other state-of-the-art algorithms. We selected and implemented two approaches: static thresholding and the OTSU method detailed in Sect. 2. The images on which the evaluation was made are chosen for their complexity. The algorithms selected have given very poor results and only select pixels with high luminosity. Until today, no approach is able to extract the markings well under different conditions. From Table 1 and the images in Fig. 6, we can easily conclude that our algorithm is robust and accurate especially under severe experimental conditions.

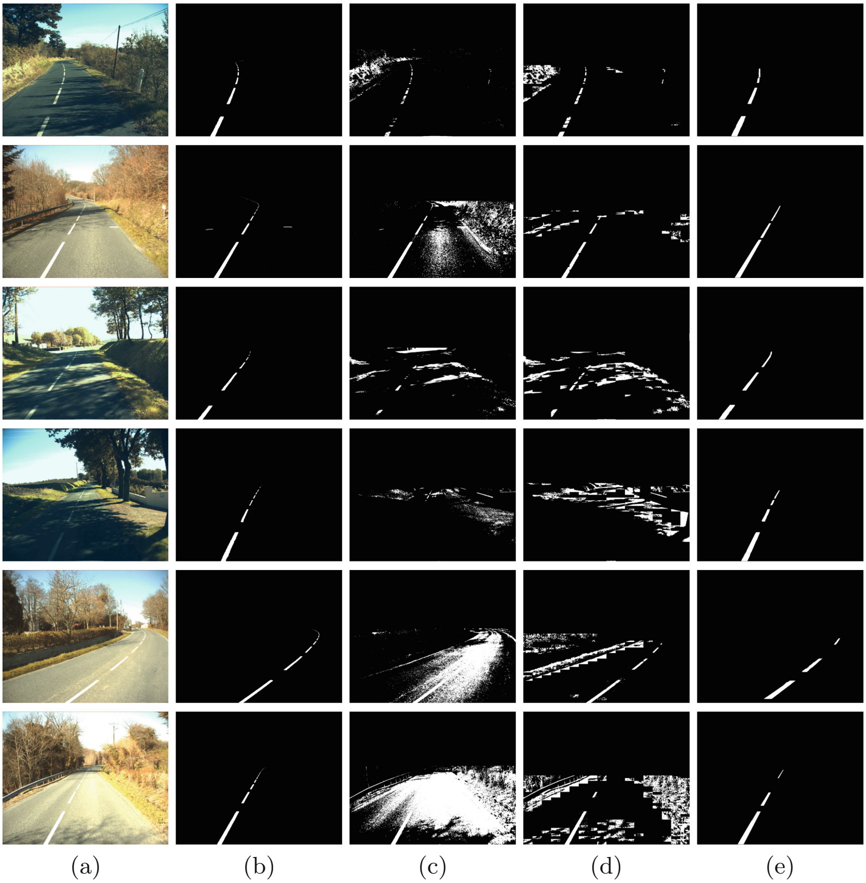


Fig. 6. Visual comparison of our algorithm with other methods. (a) original images (b) ground truth (c) progressive threshold method (d) optimized otsu method (e) our approach.

5 Conclusion

In this paper, we represented a new algorithm of moving and stationary object extraction based on improving declivity. Different algorithms have been implemented to improve the quality of markings extraction, each of them bring some improvements in one sense.

The experimentation showed that the method is applicable in real-world and complex scenes. The foreground extraction method is based on two-dimensional declivity. It has already been evaluated in terms of precision on a set of images from the "ROMA" database. Real-world datasets have been shot at four different environments, including a hundred scenario per place under different illumination and weather conditions.

Future improvements will consider machine learning methods in order to learn a model of the different types, forms, appearances, etc.

References

1. Hwang, S., Kim, N., Choi, Y., Lee, S., Kweon, I.S.: Fast multiple objects detection and tracking fusing color camera and 3D LIDAR for intelligent vehicles. In: International Conference on Ubiquitous Robots and Ambient Intelligence (URAI), Sotitel Xian on Renmin Square, Xian, China, 19–22 August 2016
2. Yousif, T.M., Alharam, A.K., Elmedany, W., AlKhalaf, A.A., Fardan, Z.: GPRS-based robotic tracking system with real time video streaming. In: 4th International Conference on Future Internet of Things and Cloud Workshops, Vienna, Austria. IEEE (2016)
3. Xiaozhu, X., Cheng, H.: Object detection of armored vehicles based on deep learning in battlefield environment. In: 4th International Conference on Information Science and Control Engineering (ICISCE), Changsha, China, 21–23 July. IEEE (2017)
4. Saleem, N.H., Klette, R.: Accuracy of free-space detection: monocular versus binocular vision. In: International Conference on Image and Vision Computing New Zealand (IVCNZ), Palmerston North, New Zealand, 21–22 November. IEEE (2016)
5. Wedde, H.F., Senge, S.: BeeJamA: a distributed, self-adaptive vehicle routing guidance approach. IEEE Trans. Intell. Transp. Syst. **14**(4), 1882–1895 (2013)
6. Magnier, V., Gruyer, D., Godelle, J.: Automotive LIDAR objects detection and classification algorithm using the belief theory. In: 2017 IEEE Intelligent Vehicles Symposium (IV), Redondo Beach, CA, USA, 11–14 June 2017
7. Nimvari, Z.E., Mosavi, M.R.: Accurate prediction of differential GPS corrections using fuzzy cognitive map. In: 3rd Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS), 20–21 December 2017
8. Xu, F., Wang, Z.: An embedded visual SLAM algorithm based on Kinect and ORB features. In: Proceedings of the 34th Chinese Control Conference, Hangzhou, China, 28–30 July 2015
9. Chen, Y., He, M.: Sharp curve lane boundaries projective model and detection. In: 10th International Conference on Industrial Informatics (INDIN), Beijing, China, 25–27 July. IEEE (2012)
10. Basri, R., Rivlin, E., Shimshoni, I.: Image-based robot navigation under the perspective model. In: Proceedings of International Conference on Robotics and Automation, Detroit, MI, USA, 10–15 May 1999

11. Bali, A., Singh, S.N.: A review on the strategies and techniques of image segmentation. In: Fifth International Conference on Advanced Computing and Communication Technologies, Haryana, India, 21–22 February. IEEE (2015)
12. Kwon, D.: An image segmentation method based on improved watershed algorithm. In: International Conference on Computational and Information Sciences (ICCIS), Chengdu, China, 17–19 December. IEEE (2010)
13. Otsu, N.: A threshold selection method from gray-level histograms. IEEE Trans. Syst. Man Cybern. **9**(1), 62–66 (1979)
14. Tang, G.: Road recognition and obstacle detection based on machine vision research, pp. 14–19 (2005)
15. Huang, J., Liang, H., Wang, Z., Mei, T., Song, Y.: Robust lane marking detection under different road conditions. In: International Conference on Robotics and Biomimetics (ROBIO), China, 12–14 December 2013. IEEE (2013)
16. Huang, J., Liang, H., Wang, Z., Song, Y., Deng, Y.: Lane marking detection based on adaptive threshold segmentation and road classification. In: Proceedings of the International Conference on Robotics and Biomimetics, 5–10 December 2014. IEEE (2014)
17. Michi, P., Debrie, R.: Fast and self-adaptive image segmentation using extended declivity. Ann. Télécommun. **50**(3–4), 401 (1995)
18. Elhassouni, F., Ezzine, A., Alami, S.: Modelisation of raindrops based on declivity principle. In: 13th International Conference Computer Graphics, Imaging and Visualization (CGiV), 29 March–1 April 2016. IEEE (2016)
19. Yan, X., Li, Y.: A method of lane edge detection based on canny algorithm. In: Chinese Automation Congress (CAC), 20–22 October 2017
20. Jung, C.R., Kelber, C.R.: A robust linear-parabolic model for lane following. In: Proceedings of 17th Brazilian Symposium on Computer Graphics and Image Processing, pp. 72–77. IEEE (2004)
21. Takahashi, A., Ninomiya, Y., Ohta, M., Nishida, M., Yoshikawa, N.: Image processing technology for rear view camera (1): development of lane detection system. R&D Rev. Toyota CRDL **38**(2), 31–36 (2003)
22. Niu, J., Lu, J., Xu, M., Lv, P., Zhao, X.: Robust lane detection using two-stage feature extraction with curve fitting. Pattern Recogn. **59**, 225–233 (2016)