

CIEL * C * h 를 이용한 조도변화에 강인한 차선 인식 연구

호세*, 조윤지*, 손광훈*

*연세대학교 전기전자공학부

e-mail : pineda@yonsei.ac.kr, cyjwisdom@naver.com, khsohn@yonsei.ac.kr

Illumination-Robust Lane Detection Algorithm using CIEL * C * h

Jose Angel Pineda*, Yoon-Ji Cho*, Kwang-hoon Sohn*

*Dept. of Electrical and Electronic Engineering, Yonsei University

Abstract

Lane detection algorithms became a key factor of advance driver assistance system (ADAS), since the rapidly increasing of high-technology in vehicles. However, one common problem of these algorithms is their performance's instability under various illumination conditions. We recognize a feasible complementation between image processing and color science to address the problem of lane marks detection on the road with different lighting conditions. We proposed a novel lane detection algorithm using the attributes of a uniform color space such as CIEL*C*h with the implementation of image processing techniques, that lead to positive results. We applied at the final stage Clustering to make more accurate our lane mark estimation. The experimental results show the effectiveness of our method with detection rate of 91.80%. Moreover, the algorithm performs satisfactory with changes in illumination due to our process with lightness (L^*) and the color's property on CIEL*C*h.

1. Introduction

Recently studies show that road accidents due to the driver factors takes over the fifty percent of the crashes that happens on the road [1]. Many efforts have been done to create an efficient and effective system to help drivers with this task. The incorporation of control units in the automotive industry has enhanced the safety of passengers and pedestrians by including innovative technologies and modules such as radar, sensor, lidar or cameras [2]. The advanced driver assistance system(ADAS) plays a vital role in the prevention of vehicle's accidents, providing a support to the drivers based on intelligence sensors and technologies. However, these technologies also present disadvantage, and even a combination of them certainly cannot guarantee the safety of the human life. Therefore, the development of new applications is essential to ensure the protection of drivers and pedestrian on the road. Over the last decade, lane detection algorithms have gathered more importance and have been proposed to provide a significant assistance to drivers and decrease the accidents for driver reason. Almost all lane detection algorithms are dealing by converting the images to gray scale. [3] preprocessed the RGB images and converted to gray scale after applying Sobel edge detection. For detecting lane boundaries, they applied hough transform and set the region of interest (ROI), as before [4] changes the images to gray scale, edges enhancement and Canny edge detection were applied and improved hough transform detects the final lanes. Other methods decided to use lane color information, [5] and [6] are based on YCbCr color space, while [7] uses HVS color space. Those color space mentioned before are not uniform, and then cannot precisely calculate the color difference. Nonetheless, no one has developed an algorithm which takes advantage of uniform color space and its attributes. Uniform color spaces are

representation of color perception in three-dimensional space, which the color difference can be measured correctly. [8] proposed an edge detection using CIELAB, however they only substrate the a^* channel from gray scale image to eliminate the reddish-greenish color considered noise in the image and detect the edges in the difference image. The Commission Internationale d'Eclairage (CIE) recommended the use of two approximately uniform color spaces and associated color-difference formulae, CIE 1976 $L^*a^*b^*$ Space [9], also known as CIELAB. CIELAB is consists of Cartesian coordinates system, which the axis L^* represents Lightness, the axis a^* defines redness-greenness, and the axis b^* defines yellowness-blueness. CIELAB color stimuli in cylindrical coordinates is useful to address the lane detection problem, therefore two attributes of color are computed from $L^*a^*b^*$ attributes, chroma (C_{ab}^*) represents the Euclidian distance from lightness-axis to the point under a^*-b^* plane, and hue angle (h_{ab}) that is an angle between the reference and C^* -axis, this attributes denotes as CIEL*C*h.

In this paper, we propose a novel road lane detection algorithm using CIE L^*C^*h color space, which performs well under different illumination conditions due to the uniformity of the color space and its attributes, in which road lanes are straightforward recognized from images. The input image is processed on the CIE L^*C^*h color space, in one hand lightness is used to detect the white lane after image enhancement with a variation of Adaptive Histogram Equalization(CLAHE), in the other hand, hue angle and chroma are essential and required for the detection of the yellow lanes. Canny edge detection is applied for his well performances dealing with noise, and Hough transform [10] to detect straight lines with angles' constraint, after agglomerative Hierarchical Clustering [11] process, the final road lanes marks are presented.

2. Proposed Method

Our proposed algorithm combines advantage of uniform color space, its attributes and images processing techniques to achieve a novel illumination-robust lane detection based on CIE L*C*h. we addressed the road lane detection problem by processing color images on CIE L*C*h, it is shown that road lanes can be effectively segmented from images using the attributes of uniform color space. CIE L*C*h is represented as three-dimensional color space defines with lightness, chroma and hue angle. Our method begins by converting color images to sRGB, next to CIE XYZ, later to CIE L*a*b*, and finally to CIE L*C*h color space, where we process the images for detecting lanes. The overall algorithm for the road lane detection is shown in Fig. 1, details of each process are presented as follows.

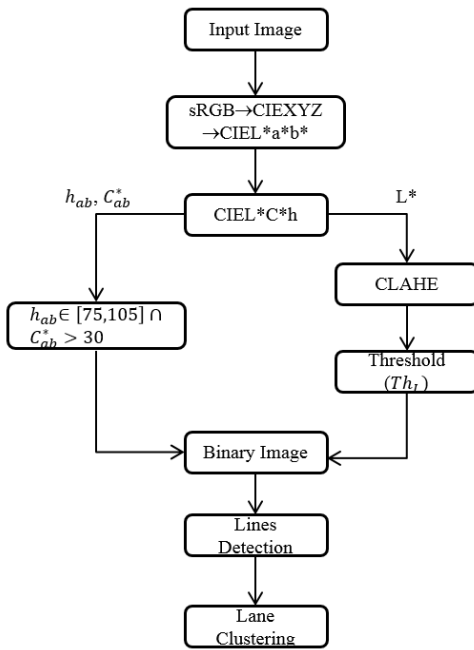


Fig. 1: Flowchart of the proposed method.

A. White Lane Detection on CIE Lightness

Lightness or L*, is the attribute of CIE L*C*h color space which provides an approximately uniform scale of perceived lightness under average viewing conditions [12], and it is reasonably similar to how humans perceive the lightness from objects. The range of lightness is from 0 to 100, where 0 means black and 100 means white (Fig. 2). The white lanes can be effectively detected by using the characteristic of lightness attribute, which pixels with high values (half-top, $L^* > 50$) have similar color and close to white, then those pixels are more likely to belong to the white lanes on the road. Hence, we made a discrimination in lightness to segment the white road lane from others that are part of the images. We applied Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance the contrast of the image and create strong edges between lanes and the road (Fig. 3), besides it has acceptable performance in presence of noise. Therefore, the binary image is created by setting a threshold on Lightness as shown in the following equation:

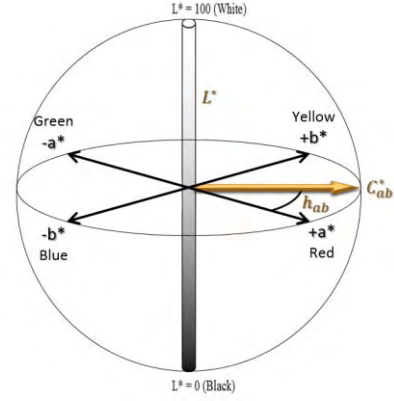


Fig. 2. CIE L*C*h: lightness, chroma and hue angle.

$$H_L(r) = \sum_{r=0}^{100} \text{Hist}_L(r) \quad (1)$$

$$B(x, y) = \begin{cases} 1, & \text{if } H_L(L^*(x, y)) > Th_L \\ 0, & \text{otherwise} \end{cases}$$

Where $H_L(r)$, $\text{Hist}_L(x)$, $B(x, y)$, $L^*(x, y)$, r , and Th_L are the cumulative histogram, histogram, binary image, lightness intensity and lightness threshold value respectively. We defined the threshold value up to keep the top 10% of pixels in the top of L*-axis, as explained above, this corresponds to the pixels that are closely to the white color, and then belong to the white lane (see Fig. 4). Since we use CLAHE, the threshold value depends of the histogram, then it adapts for each image related to its histogram.



Fig. 3: (a) Lightness channel, (b) contrast enhancement with CLAHE.

B. Yellow Lane Detection using Chroma Value and Hue Angle

Every image is transformed to CIE L*C*h color space, the chroma (C_{ab}^*) is seen geometrical as the radial vector (Euclidian distance) that starts at the L*-axis and finishes on the chroma value, plane a*-b*. The hue angle (h_{ab}) represents the angle of the vector C_{ab}^* with the reference, which takes values from 0° to 360° , units of degree, and usually measures as anti-clock wise. Besides, it's a useful attribute for specifying hue numerically. Hence, both quantities can be calculated from the components a* and b* of CIE L*a*b*, their equations are as follows:

$$C_{ab}^* = [(a^*)^2 + (b^*)^2]^{1/2} \quad (2)$$

$$h_{ab} = \arctan\left(\frac{b^*}{a^*}\right)$$

Where C_{ab}^* , h_{ab} are defined as chroma and hue angle

respectively. We can settle from the experimental results that yellow lanes on the road have constant values of hue angle around 90° under different illumination conditions. Moreover, chroma is greater than 30 units. Thus, we successfully recognized yellow lanes from the images using the knowledge explained above, and created a range of hue angle. We defined it as a change in angle of 15° by experimental results (see Fig. 5). The binary image for yellow lanes was obtained from pixels that satisfy both conditions, as shown in the next equation:

$$B(x, y) = \begin{cases} 1, & \text{if } 75^\circ < h_{ab}(x, y) < 105^\circ \text{ and} \\ & C_{ab}^*(x, y) > 30 \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

Where $h_{ab}(x, y)$ is the hue angle in degree, $C_{ab}^*(x, y)$ is the normalized chroma value, and $B(x, y)$ is the binary image (Fig. 6), at the pixel with coordinate (x, y) respectively.



Fig. 4: Binary image for white lane

C. Lane Clustering stage

As previous process in this stage, similar to [3], we applied constraint in the angles to remove incorrect straight lines detected by Hough Transform, we defined it as in the following equation:

$$Q = \{I_B(x_i, y_i) = 255, |\theta(x, y)| \in [10^\circ, 75^\circ]\} \quad (4)$$

Where Q represents the correct straight lines, B is the binary image, θ is the angle that straight lines make with the reference. We empirically define the range of angle for the correct lane marks to $[10^\circ, 75^\circ]$ for positive, and $[-10^\circ, -75^\circ]$ for negatives, respectively. Thus, we used agglomerative Hierarchical Clustering to create groups of similar lines detected by Hough Transform. One advantage of this method is that the number of cluster generated depends on the inconsistency presented in the links of the cluster tree (see Fig. 7), besides a proper threshold can be settled to identify the divisions where similarities between lanes change abruptly. Then, we computed the Euclidian distance from each of lines to generate groups (clusters) of similar straight lines. The clustering process, as mentioned on [12], begins by considering each sample of data in the general case, lines for our specific problem, represents one cluster. Hence, according to the similarity of the lines, we linked them in pairs to create a new cluster made up of two lines, we generated bigger clusters linking the newly formed clusters to each other, until all the lines detected by Hough Transform are linked together, these results are well-known as hierarchical tree. The inconsistency coefficient between linked clusters determines the number and the well partition of clusters. Hence, we took the average of lines over each well-separated cluster (see Fig. 8).

similar lines detected by Hough Transform. One advantage of this method is that the number of cluster generated depends on the inconsistency presented in the links of the cluster tree (see Fig. 7), besides a proper threshold can be settled to identify the divisions where similarities between lanes change abruptly. Then, we computed the Euclidian distance from each of lines to generate groups (clusters) of similar straight lines. The clustering process, as mentioned on [12], begins by considering each sample of data in the general case, lines for our specific problem, represents one cluster. Hence, according to the similarity of the lines, we linked them in pairs to create a new cluster made up of two lines, we generated bigger clusters linking the newly formed clusters to each other, until all the lines detected by Hough Transform are linked together, these results are well-known as hierarchical tree. The inconsistency coefficient between linked clusters determines the number and the well partition of clusters. Hence, we took the average of lines over each well-separated cluster (see Fig. 8).

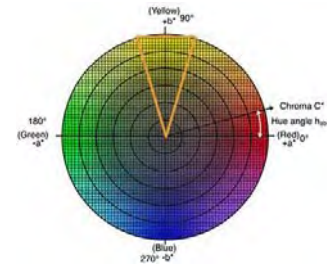


Fig. 5: The plane a^*-b^* with our constraint of hue angle.

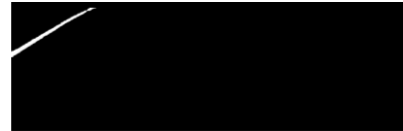


Fig. 6: Binary image for yellow lane

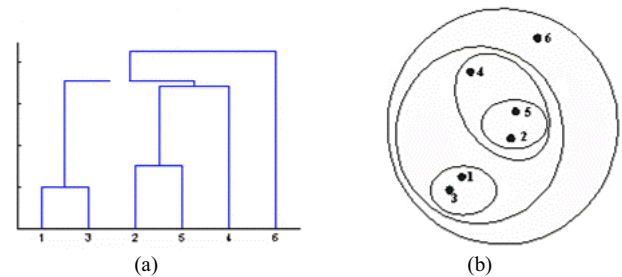


Fig. 7: (a) Dendrogram, (b) Venn diagram representation.



Fig. 8: (a) lines detected, (b) average of lines in each cluster.

3. Experimental Results

The effectiveness of Vision-based ADAS methods can be measured by datasets in different environmental and illumination conditions respectively. Algorithms that keep their performances under different changes of lights are called as illumination-robust systems. The lights change due to some external factors, i.e. images taken with daylight, the time and weather have a strong influence in the illumination. In the other hand, images taken at night, light changes because of streetlamps or vehicles lamps [5]. We used the DIML-1 dataset which includes images from various conditions of light, taken with daylight and night time. An OV10630 image sensor was utilized to acquire the DIML's dataset1, and provides images with 1280x800 resolution at 15 frames per second. The proposed method performed well under various illumination conditions, which the lane detection results are shown in the Fig. 9. We measured the detection rate with a visual inspection by a single user. We defined three categories for our results, and described them as follows: (i) correct detection, which the lanes are well-detected and marked in the right position on the road; (ii) incorrect detection, which lane marks estimation are in an area that don't correspond to be in the image; (iii) missed detection, the algorithm does not recognize the lanes and there is not lane mark estimation. The detection rate is

computed by the following equation:

$$D_R = \frac{C}{N} * 100 \quad (\%) \quad (5)$$

Where D_R , C , and N represent the detection rate, the number of correct detection, and the number of total frames, respectively. The average detection rate was 91.80% as summarized in Table 1.

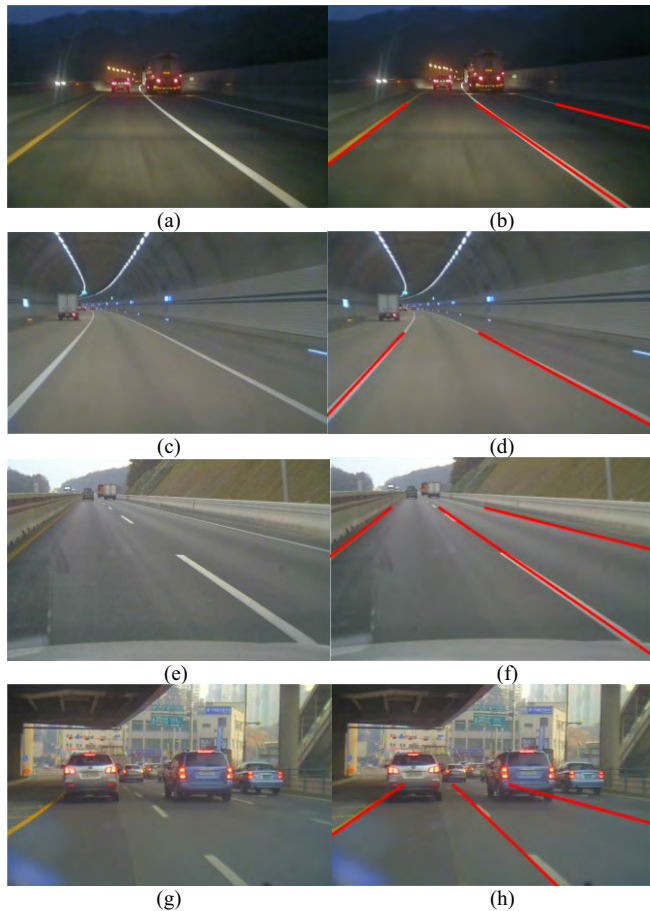


Fig. 9: (a), (c), (e) and (g) are the input images. (b), (d), (f) and (h) are our proposed method outputs for highway-night, tunnel, highway-day and urban-day, images respectively.

<Table 1> Lane detection rate of the proposed algorithm in various environments

Dataset	Highway-Day	Highway-Night	Urban-Day	Tunnel	Total
Total frames	1329	814	507	385	3035
Detected frames	1215	734	486	351	2786
Detection rate (%)	91.42	90.17	95.85	91.17	91.80

4. Conclusion

In this paper, we addressed the problem of road lane detection for driver assistance. Moreover, we considered the problem of various illumination conditions. Usually the performance of lane detection algorithms suffers with changes of lights, we proposed an algorithm that keep the

performance under different lighting environments. We effectively detected the lanes on the road, by using the properties and attributes of the CIEL*C*h color space. The experimental results show that our algorithm adapts well to the changes of lights. In future work, we plan to detect the blue road lane as well as to optimize our algorithm for real-time application. In addition, we will study the possibility to detect automobiles or pedestrian by an extension of our method to those tasks.

References

- [1] C.P. Ramnath, S.Y. Kanawade. "Advanced Driver Assistance System (ADAS)". International Journal of Advanced research in Electronics and Communication Engineering, Vol. 4, Issue 10, Oct. 2015.
- [2] A. Ziebinski, R. Cupek, H. Erdogan, S. Waechter, "A Survey of ADAS Technologies for the Future Perspective of Sensor Fusion". International Conference on Computational Collective Intelligence, ICCCI 2016, pp 135-146.
- [3] R. Okuda, Y. Kajiwara, K. Terashima, "A Survey of Technical Trend of ADAS and Autonomous Driving". International Symposium on VLSI Technology, Systems and application (VLSI-TSA), 2014.
- [4] Y. Kortli, M. Marzougui, B. Bouallegue, J. Subash, P. Rodrigues, M. Atri, "A Novel Illumination-Invariant Lane Detection System". 2nd International Conference on Anti-Cyber Crimes (ICACC), 2017.
- [5] J. Son, H. Yoo, S. Kim, K. Sohn, "Real-time Illumination Invariant Lane Detection for Lane Departure Warning System" Expert Systems with Applications, Vol. 42, Issue 4, pp 1816-1824, 2015.
- [6] J. Baili, M. Marzougui, A. Sboui, S. Lahouar, M. Hergli, J. Subash, K. Besbes, "Lane Departure Detection Using Image Processing Techniques". 2nd International Conference on Anti-Cyber Crimes (ICACC), 2017.
- [7] A. Borkar, M.T.Smith, and M. Hayes, "Robust lane detection and tracking with RANSAC and Kalman Filter" IEEE International Conference on Image Processing, pp. 3261-3264, 2009.
- [8] H. Fan, W. Wang, "Edge Detection of Color Road Image Based on Lab Model". 5th International Conference on Computational and Information Sciences (ICCIS), 2013.
- [9] Wyszecky & Stiles, "Color Science", 2nd edition.
- [10] R. Duda, P. Hart "Use of the Hough transformation to detect lines and curves in pictures" Commun. ACM, vol.15, no. 1, pp 11-15, Jan 1972.
- [11] R. Hota, S. Syed, S. Bandyopadhyay, P. Radhakrishna, "A Simple and Efficient Lane Detection using Clustering and Weighted Regression", 15th International Conference on Management of Data COMAD 2009.
- [12] R.H.G. Hunt, "The Reproduction of Color", 6th edition.