第 47 卷 第 12 期
2020 年 12 月

湖南大学学报（自然科学版）
Journal of Hunan University (Natural Sciences）

Vol. 47. No. 12.
Dec. 2020

Open Access Article

Road Detection Based on Statistical Analysis

I Komang Somawirata[1], Kartiko Ardi Widodo[1], Sentot Achmadi[1], Fitri Utaminingrum[2]

[1] Department of Electrical Engineering, National Institute of Technology (ITN Malang), Indonesia

[2] Computer Vision Research Group, Faculty of Computer Science, Brawijaya University, Malang, Indonesia

Abstract: Vision-based road detection is a challenging topic in the field of autonomous vehicles. Road information is needed for a robot vehicle to control their movement while driving. The aim of this study is to make a simple and fast road detection system which can be used to control vehicle robots in real-time. This paper proposes real-time road detection, which begins from images captured on a camera, then pre-processing and road detection based on color and statistical analysis, for reducing the detection failure rate. The dataset used for the system was taken from urban roads. The color-matching procedure uses minimum/maximum matching between the dataset and sample pixels of captured images. At the same time, the captured images are clustered by a grid method, grouping pixels having the same size between grid cluster and dataset. PSNR and MSSIM are used for analyzing the similarity of the grid cluster and dataset. We implemented a threshold value to determine if the PSNR and MSSIM analysis result is a road. From our experiment, we obtain a threshold value of 85 db for PSNR and 0.90 for MSSIM. If the both analyses result in values greater than their threshold values, then the result is voted to be a road. Finally, the road is determined by analyzing the result of color and statistical analysis. The system will determine there is a road if the both analyses detect the road. The result shows the color based road detection resulting file detection caused by changing the lighting and the color of the road. We have solved that problem by implementing PSNR and MSSIM analysis in the grid clustering method. The result of the proposed method has been presented in this paper, and can potentially reduce the failure rate of detection using the color-based method.

Keywords: road labeling, image measurement, mean structural similarity index measurement.

基于统计分析的道路检测

摘要：在自动驾驶汽车领域，基于视觉的道路检测是一个具有挑战性的话题。机器人车辆在行驶时需要控制其运动的道路信息。这项研究的目的是开发一种简单，快速的道路检测系统，该系统可用于实时控制车辆机器人。本文提出了一种实时道路检测方法，该方法从摄像机捕获的图像开始，然后基于颜色和统计分析进行预处理和道路检测，以降低检测失败率。该系统使用的数据集取自城市道路。颜色匹配过程使用数据集和捕获图像的样本像素之间的最小/最大匹配。同时，通过网格方法对捕获的图像进行聚类，在网格聚类和数据集之间对具有相同大小的像素进行分组。信噪比和 MSSIM 用于分析网格集群和数据集的相似性。我们实现了一个阈值，以确定信噪比和 MSSIM 分析结果是否是道路。从我们的实验中，我们获得的阈值对于信噪比为 85 db，对于 MSSIM 为 0.90。如果两个分析的结果均大于其阈值，则将结果投票为道路。最后，通过分析颜色结果和统计分析来确定道路。如果两个分析都检测到道路，则系统将确定存在道路。结果显示了由于改变道路的照明和颜色而导致的基于颜色的道路检测结果文件检测。我们通过在网格聚类方法中实施信噪比和 MSSIM 分析解决了该问题。本文提出了该方法的结果，可以潜在地降低基于颜色的方法的检测失败率。

关键词：道路标记，图像测量，平均结构相似性指标测量。

Received: November 5, 2020/ Revised: November 20, 2020/ Accepted: December 20, 2020/ Published: December 25, 2020

Fund Project: Research grant PTUPT DRPM Direktorat Jenderal Riset dan Pengembangan Kementerian Riset, Teknologi, dan Pendidikan Tinggi, Indonesia.

About the authors: I Komang Somawirata, Kartiko Ardi Widodo, Sentot Achmadi, Department of Electrical Engineering, National Institute of Technology (ITN Malang), Indonesia; Fitri Utaminingrum, Computer Vision Research Group, Faculty of Computer Science, Brawijaya University, Malang, Indonesia

Corresponding author: I. Komang Somawirata, I.kmgsomawirata@lecturer.itn.ac.id

1. Introduction

Computer vision has been implemented in various fields of science, such as manufacturing, security, robotics, shopping, automotive and others. In the automotive field, computer vision is used for Autonomous Guided Vehicles (AGV) [1], early warning systems and monitoring. One challenging research topic in AGV is road detection. Camera sensors are one of the most commonly used methods for road detection. The camera produces multiple frames and by processing this data, an image is obtained. A number of methods have used to determine road area through image analysis [13]. However, various problems can occur from roads detected by a camera, such as differing light intensity, contrast and shadows.

Currently, many algorithms for road detection have been proposed by researchers, including well-paved road detection with lane markings in urban areas [2] and road detection in rural areas [3]. Road detection approaches based on vanishing point use several methods, including segmentation of dominant line [4], parallel lines [5] and texture orientation [6]. The voting scheme method is used for extracting the road [6] and the optimal strategies for selecting the road boundaries [7]. The road can be segmented (by color, texture, or feature) to cluster pixels before machine learning methods are implemented to obtain the region of the road. However, these methods have high computation times and are difficult to implement in a real-time system.

The feature-based method, which is one of the best-known methods for road detection, uses the color, texture, and edge of the road to generate the road areas in an image. In contrast, the approach model of detecting a road area uses the shape of the road by extracting the line using edge detection [8] and matching it to the road model; however, this method involves a high computational complexity and is often unable to identify changes in lighting or shadows on the road.

This paper adopts a feature-based method of color and texture and combines it with statistical analysis, such as peak signal-to-noise ratio (PSNR) and mean structural similarity index measurement (MSSIM), to reduce the fail detection of the feature-based method. The PSNR is applied because it is easy to calculate, has clear physical meanings, and is mathematically convenient. Color-based methods are particularly susceptible to light changes and in the RGB space, this will provide a very wide range of color changes. In this paper, MSSIM resolves this issue, by using the luminance component and standard deviation to measure the proximity and similarity of images.

2. Related Work

Road detection can be grouped into three methods: human-supervised, self-supervised, and unsupervised.

Human-supervised methods use machine learning algorithms and convolutional neural networks (CNNs) [9], [10], [18]. However, they involve high training costs and are unscalable for the human effort involved.

Unsupervised approaches [6], [11], [12], which generally make use of an image, use color and texture information to find a border in the image. These approaches make various assumptions, including an approximation of the shape of the road in highway scenes and the assumption that the center-bottom of the road actually belongs to the road. This paper takes an unsupervised approach that enhances the road detection performance by the implementation of PSNR and MSSIM to improve the color and texture information of the cluster area.

Self-supervised algorithms [14], [15], [16] operate between the human-supervised and unsupervised approaches. These methods need to rapidly adapt the model. The model, which is built on color-based template matching and a color-based mixture of Gaussians, also suffers model drift.

3. Proposed Method

Fig. 1 shows three steps of the proposed method: image capturing, pre-processing, and road labeling. Image capturing is the capture of an image from the camera; pre-processing consists of image resizing and image filtering; and road labeling is the defining of the road area through statistical analysis. The end result is the detection of the road.

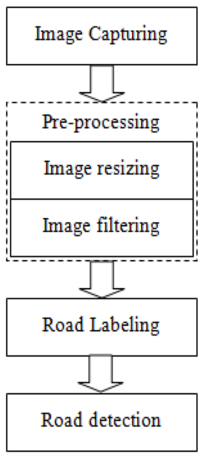


Fig. 1 Road detection process

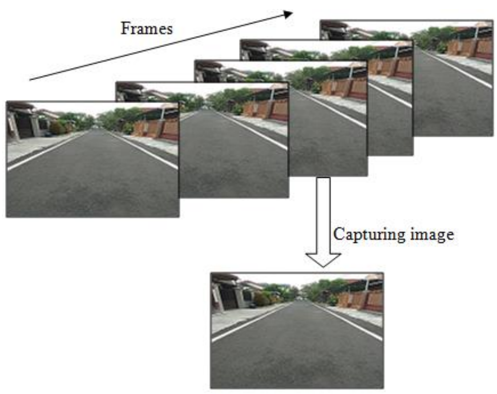


Fig. 2 Capturing image process

3.1. Image Capturing

Fig. 2 shows the process of capturing images from a camera sensor that produces multi-frame image motions. The image capturing process takes one frame and converts it into an image. The capturing image is repeated until the process of road detection is finished.

3.2. Pre-Processing

The source image from the camera produces a high-resolution image. So, the source image needs to be reduced to a smaller file size.

3.2.1. Image Resizing

This paper uses bilinear image resizing based on a weighting method. This method uses four sample pixels and four weight values to determine an interpolation pixel. The four sample pixels are symbolized by $fs(i,j)$ and the weight value is symbolized by $w(i,j)$. The weight value is obtained by a linear curve, as shown in Fig. 3. Each coordinate "*x*" and "*y*" of the linear curve has two opposing linear curves—among others are the uphill curve and the downhill curve.

The values of the window $w(i,j)$ matrix elements consistently change, depending on the position of interpolation pixel.

$$w(i,j) = \begin{vmatrix} \mu_{x1} \times \mu_{y1} & \mu_{x1} \times \mu_{y2} \\ \mu_{x2} \times \mu_{y1} & \mu_{x2} \times \mu_{y2} \end{vmatrix} \quad (1)$$

The sample pixel window of $f_s(i,j)$ is obtained from the source image. The pixel coordinates for $f_s(i,j)$ is obtained by calculating the corresponding coordinates between the target image and source image. Equation (2) is used for obtaining the corresponding coordinate.

$$c_h = \frac{n_1}{S_h} \text{ and } c_w = \frac{n_2}{S_w} \quad (2)$$

where n_1 and n_2 are the coordinates of the target image, S_h and S_w are the scaling factors of the image scaling. The sample pixel window is obtained by then rounding up and down, as in Eq. (3).

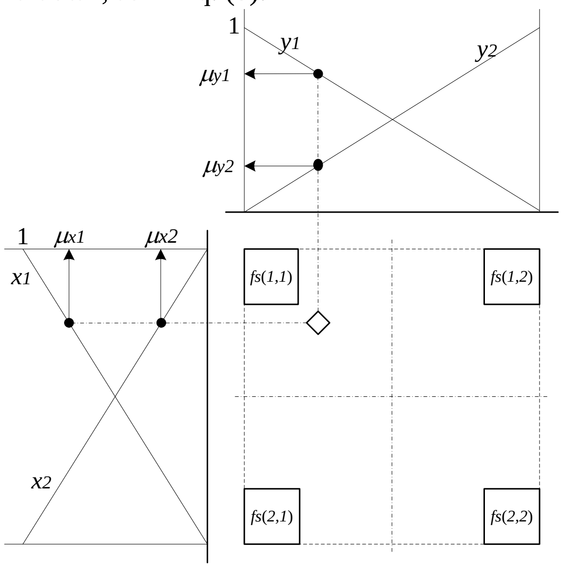


Fig. 3 Linear weighting curve

$$fs(i,j) = \begin{vmatrix} f(\lfloor c_h \rfloor, \lfloor c_w \rfloor) & f(\lfloor c_h \rfloor, \lceil c_w \rceil) \\ f(\lceil c_h \rceil, \lfloor c_w \rfloor) & f(\lceil c_h \rceil, \lceil c_w \rceil) \end{vmatrix} \quad (3)$$

where the symbol of $\lfloor\cdot\rfloor$ is rounded down and $\lceil\cdot\rceil$ is rounded up.

Image resizing is obtained by finding the sum of the multiplication matrix between the sample pixel $fs(i,j)$ and the weighting window $w(i,j)$, as seen in Eq. (4).

$$\hat{f}(x,y) = \sum_{i=1}^{2}\sum_{j=1}^{2} fs(i,j)w(i,j) \quad (4)$$

3.2.2. Image Filtering

The increase in the quality of a resized image uses a Gaussian filter. Filtering the image can be conducted by convolution of an image $\hat{F}$ with a Gaussian mask W as in Eq. (5).

$$F = \hat{F} * W \quad (5)$$

A Gaussian mask can be obtained by two-dimensional Gaussian functions, as in Eq. (6):

$$W = Ae^{-\left(\frac{(x-x_O)^2}{2\sigma_x^2} + \frac{(y-y_O)^2}{2\sigma_y^2}\right)} \quad (6)$$

3.3. Road Labeling

In this paper, we use color as information, which refers to the dataset for pre-road detection. The dataset is in RGB and is denoted by D.

$$C_{RGB} = \min(D_{RGB}) : \max(D_{RGB}) \quad (7)$$

Equation (7) expresses each channel of the dataset's color space. The dataset's range starts from the minimum pixel value ($\min(D_{RGB})$) up to the maximum pixel value ($\max(D_{RGB})$).

The road will be labeled by 1 if the pixel is in the range of locations of the color space. Equation (8) is used for mapping road and non-road pixels. A road pixel will be labeled by 1, and a non-road pixel by 0.

$$\mathbf{L} = \begin{cases} 1 & if\ F_R \in C_R\ or\ F_G \in C_G\ or\ F_B \in C_B \\ 0 & others \end{cases} \quad (8)$$

3.3.1. Peak Signal-To-Noise Ratio (PSNR)

The peak signal-to-noise ratio (PSNR) is generally used for measuring image quality. Measurement involves two images of the same size, namely a good-quality reference image and the image to be measured. A high PSNR value indicates a good-quality image and vice versa. Furthermore, the PSNR can be used for measuring the similarity between two images, with a reference image and a measured image. The PSNR value is calculated by Eq. (9), where M denotes the number of rows in the image matrix, N is the number of columns in the image matrix, $f(x,y)$ is the reference image, and $fo(x,y)$ is the measured image.

$$PSNR = 10\log \frac{255^2 \times M \times N}{\sum_{y=1}^{M}\sum_{x=1}^{N}\left(f(x,y) - f_0(x,y)\right)^2} \qquad (9)$$

3.3.2. Structural Similarity (SSIM)

The structural similarity (SSIM) index [17] measures the similarity between two images, namely a reference image and a measured image. Both images have the same size. The measurement of two images (*x* and *y*) is done by three components, namely the Luminance ratio, the comparison of the standard deviation between *x* and *y*, and signal normalization.

The luminance of the images is measured by comparing the luminance of *x* and *y* signals that we symbolized by *l(x,y)*. The luminance value in a signal can be expressed as mean intensity (μ). Mean intensity of images *x* and *y* can be formulated in equations (10) and (11).

$$\mu_x = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad (10)$$

$$\mu_y = \frac{1}{N}\sum_{i=1}^{N} y_i \qquad (11)$$

The second component is the comparison of the standard deviation between σ_x and σ_y, expressed by equation (16). The standard deviation of σ_x can be calculated by equations (12) or (13), while the standard deviation σ_y can be calculated by equations (14) or (15).

$$\sigma_x = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - \mu_x\right)^2} \quad \text{or} \qquad (12)$$

$$\sigma_x^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - \mu_x\right)^2 \qquad (13)$$

$$\sigma_y = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(y_i - \mu_y\right)^2} \quad \text{or} \qquad (14)$$

$$\sigma_y^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(y_i - \mu_y\right)^2 \qquad (15)$$

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - \mu_x\right)\left(y_i - \mu_y\right) \qquad (16)$$

The structural similarity index measure (SSIM) of *x* and *y* can be written as in equation (17), while the mean of SSIM is presented in equation (18).

$$SSIM(x,y) = \frac{\left(2\mu_x\mu_y + C_1\right)\left(2\sigma_{xy} + C_2\right)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)} \qquad (17)$$

$$MSSIM(X,Y) = \frac{1}{M}\sum_{j=1}^{M} SSIM\left(x_j, y_j\right) \qquad (18)$$

3.3.3. Image Clustering and Cluster Road Detection

We used image clustering, which is based on the grid method. An image is clustered in the same size as shown in Fig. 4.

A data set is needed to be able to use PSNR and MSSIM as a road detector. The data set is obtained from the sample roads, which are similar to the road data being tested. Measurement by PSNR and MSSIM involves data from two images of the same size and dimensions. So, in this application, the image size in the cluster area must have the same size and dimensions as the data set image. Fig. 4 shows a sample of cluster area and a data set that will be measured by PSNR and MSSIM.

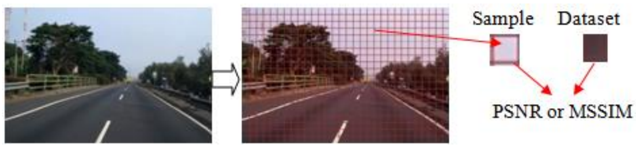
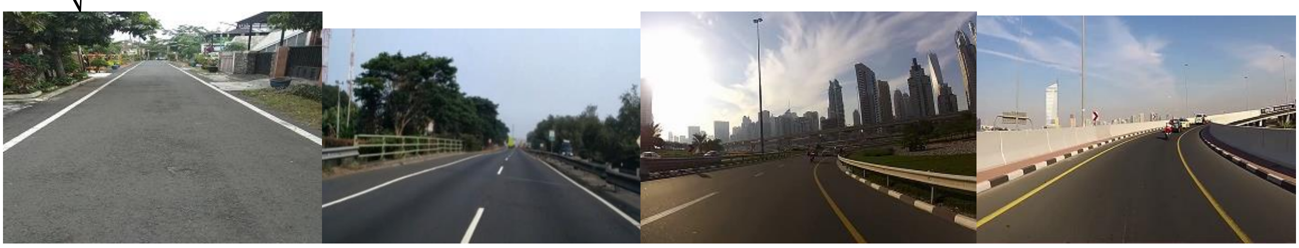
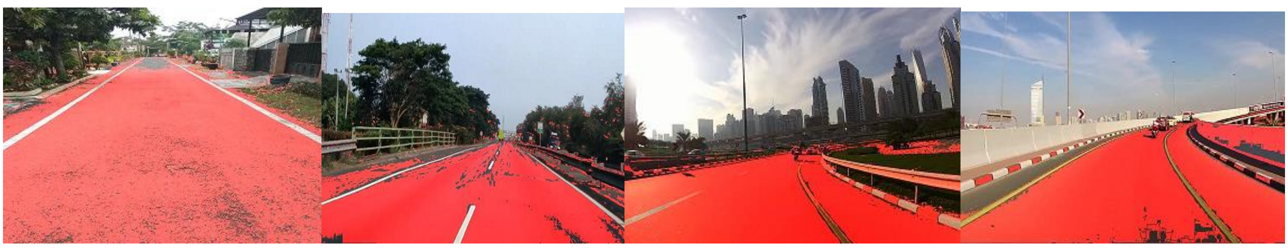


Fig. 4 Image grid clustering and analysis method



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



(e) (f) (g) (h)

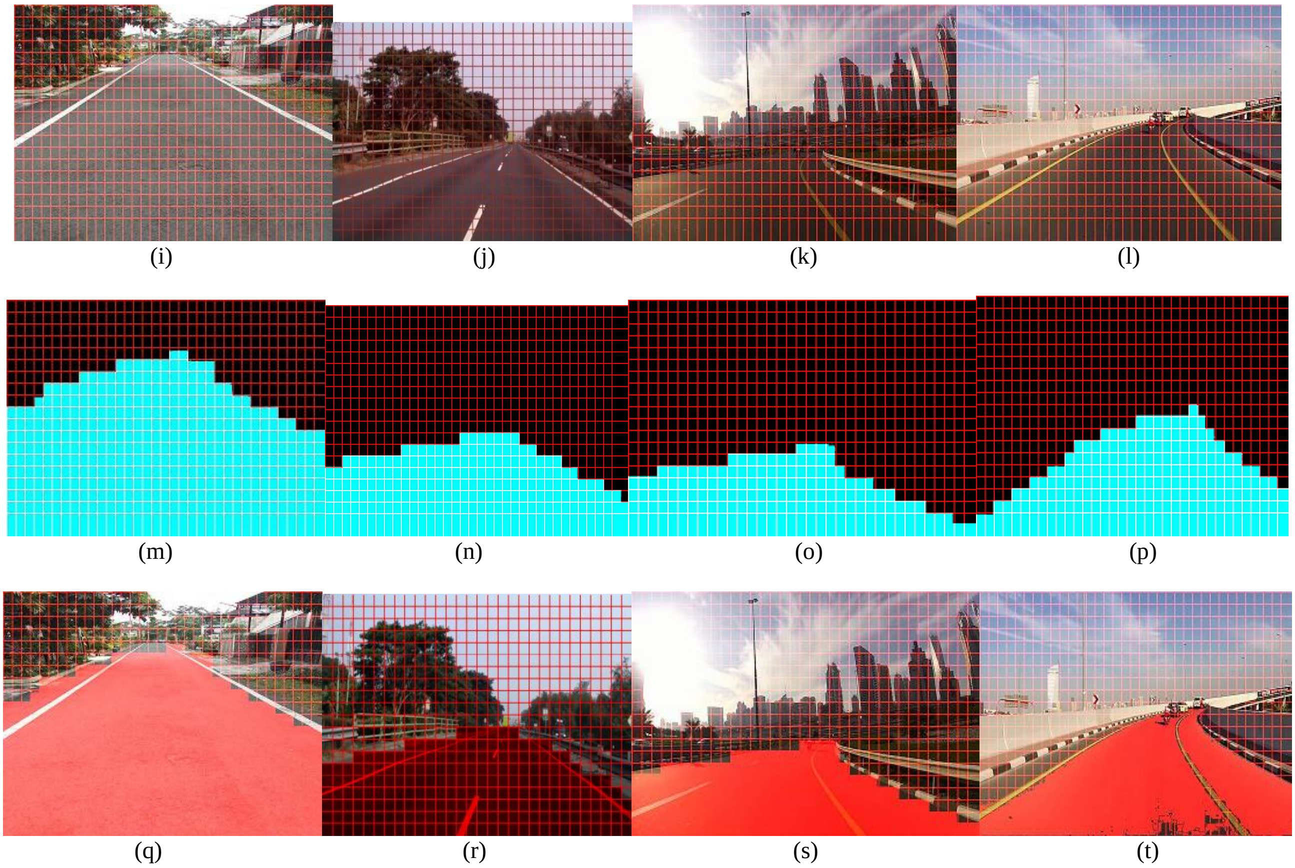


Fig. 5 The result of road detection based on color information and statistical analysis: (a) up to (d) is the source image, (e) up to (h) is the result of color based road detection, (i) up to (l) is image griding, (m) up to (p) is the result of MSSIM and PSNR mapping, (q) up to (t) is the mapping of grid map on the source image

Each cluster is analyzed by PSNR and MSSIM. If the analysis result is greater than 85 dB for PSNR and 0.90 for MSSIM, then a cluster area will labeled 1, and vice versa, if it has a smaller value, it will be labeled 0. The final conclusion of whether it is a road is formed by analyzing the result of color and statistical analysis. The system will decide it is a road if the both analyses detect the road.

4. Results and Analysis

In this part, we discussed the experimental result of the proposed method. Table 1 shows the sample of visual analysis using SSIM map and quantitative analysis using PSNR and MSSIM. Visually, the SSIM map will result in a white color if the sample grid area and the data set are the same color. In other words, if the MSSIM value is close to 1, that will result in a white color, and vice versa, if the MSSIM is close to 0, that will produce a dark color in the MSSIM map.

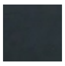
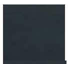
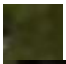
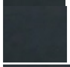
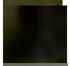
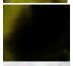
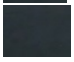
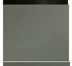
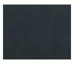
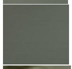
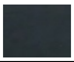
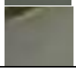
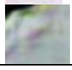
Let's look at an example of the analysis results for a cluster with the data set in Table 1. In the first, second and third examples, we present an example of a non-road in the cluster area. Visually, between the data set and sample grid data, they have very different colors and textures, so the MSSIM and PSNR analysis results will have a small value. The value of MSSIM is less than 0.6 and PSNR is less than 0.5 dB. Therefore, if we visualize it using an MSSIM map, a dark image will show. In examples four through six, we present examples of an area with road clusters. In this example, the cluster area and the dataset are similar. So, when we analyzed it, it had a large value: for MSSIM it had a value greater than 90, and for PSNR it had a value greater than 85 dB. Therefore, the visualization result using the MSSIM map will show a white image.

The proposed method was tested on five videos containing road objects. The frame is captured and then converted to an image. Fig. 5 shows the result of road detection in one frame. Figs. 5(a) to 5(d) are the source images that will be processed. Pre-processing by using color information is shown in Figs. 5(e) to 5(h). In these results, there is still some error detection, which detects a non-road as the road.

Firstly, the image is segmented in order to be analyzed using PSNR and MSSIM. Figs. 5(i) to 5(l) show the segment of *an image* on a grid. The size of *the grid* is the same as the data set. Each grid will be analyzed using PSNR and MSSIM. If they have a value greater than their threshold value, then all the regions in the grid area are labeled '1'. Figs. 5(m) to 5(p) show the result of statistical analysis using a combination of PSNR and MSSIM. If the image in Figs. 5(m) to 5(p) is mapped in their source image this will result in the image in Figs. 5(q) to 5(t).

Table 1 The sample of grid analysis using MSSIM and PSNR

No.	Dataset	Sample	SSIM	MSSIM	PSNR	Vote

		Grid	Map			
1				0.3995	41 dB	Non-road
2				0.4478	47 dB	Non-road
3				0.5113	49 dB	Non-road
4				0.9219	89 dB	Road
5				0.9519	93 dB	Road
6				0.9109	86 dB	Road

The limitation of the proposed method is that if the real road image does not match the dataset, an error will occur. The solution can be provided by updating the dataset according to the current road data.

5. Conclusion

This paper proposed road detection with a combination of color–space matching and statistical analysis. Color–space matching is used for road pre-detection and statistical analysis to reduce failure detection in pre-road detection. The color matching method results in a fail in areas that are the same color as the dataset. The combination of PSNR and MSSIM makes it possible to reduce fail detection in the color matching method. The threshold value is obtained by experiment and the results are 85 dB for PSNR and 0.90 for MSSIM. The grid area is voting as a road if they have a PSNR greater than 85 dB and an SSIM greater than 0.90. The result of the proposed method has been presented in this paper and is capable of reducing fail detection with the color-based method.

In future work, we will provide a solution for the limitation of the proposed method by adding a sensor laser radar such as a Lidar sensor. So, by combining a camera and a Lidar sensor, we hope to increase the performance of our proposed method.

References

[1] SOMAWIRATA I. K., & UTAMININGRUM F. Road Detection Based on the Color Space and Cluster Connecting. Proceedings of the International Conference on Signal and Image Processing, Beijing, 2016, pp. 118-122. https://doi.org/10.1109/SIPROCESS.2016.7888235

[2] FRITSCH J., KUHNL T., and GEIGER A. A New Performance Measure and Evaluation Benchmark for Road Detection Algorithms. Proceedings of the International IEEE Conference on Intelligent Transportation Systems, The Hague, 2013, pp. 1693-1700. https://doi.org/10.1109/ITSC.2013.6728473

[3] KONG H., AUDIBERT J.-Y., and PONCE J. Vanishing point detection for road detection. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Miami, Florida, 2009, pp. 96-103. https://doi.org/10.1109/CVPR.2009.5206787

[4] DING W., & LI Y. Efficient Vanishing Point Detection Method in Complex Urban Road Environments. *IET Computer Vision,* 2015, 9(4): 549-558. https://doi.org/10.1049/iet-cvi.2014.0187

[5] WEILI D., YONG L., WENFENG W., and YUANYUAN Z. Vanishing point detection algorithm for urban road image based on the envelope of perpendicular and parallel lines. *Acta Optica Sinica,* 2014, 34(10): 1015002. https://doi.org/10.3788/AOS201434.1015002

[6] KONG H., AUDIBERT J.-Y., and PONCE J. General road detection from a single image. *IEEE Transactions on Image Processing,* 2010, 19(8): 2211–2220. https://doi.org/10.1109/TIP.2010.2045715

[7] ZHENG T., CHENG X., CHAO M., et al. Road Segmentation Based on Vanishing Point and Principal Orientation Estimation. *Journal of Computer Research and Development,* 2014, 51(4): 762-772.

[8] XIAOLIN L., YUFENG J., YAN G., XIAOXUE F., and WEIXING L. Unstructured road detection based on region growing. Proceedings of the IEEE 30th Chinese Control and Decision Conference, Shenyang, 2018, pp. 3451-3456. https://doi.org/10.1109/CCDC.2018.8407720

[9] YAO J., RAMALINGAM S., TAGUCHI Y., MIKI Y., and URTASUN R. Estimating drivable collision-free space from monocular video. Proceedings of the IEEE Winter Conference on Applications of Computer Vision, Waikoloa, Hawaii, 2015, pp. 420-427. https://doi.org/10.1109/WACV.2015.62

[10] LEVI D., GARNETT N., FETAYA E., and HERZLYIA I. Stixelnet: A deep convolutional network for obstacle detection and road segmentation. Proceedings of the British Machine Vision Conference, Swansea, 2015, pp. 109.1-109.12. https://dx.doi.org/10.5244/C.29.109

[11] MOHAN R. Deep deconvolutional networks for scene parsing, 2014. https://arxiv.org/pdf/1411.4101.pdf

[12] CHENG H.-Y., JENG B.-S., TSENG P.-T., and FAN K.-C. Lane detection with moving vehicles in the traffic scenes. *IEEE Transactions on Intelligent Transportation Systems,* 2006, 7(4): 571-582. https://doi.org/10.1109/TITS.2006.883940

[13] AL-ABAID S. A. F. A Smart Traffic Control System Using Image Processing: A Review. *Journal of Southwest Jiaotong University,* 2020, 55(1). https://doi.org/10.35741/issn.0258-2724.55.1.31

[14] PAZ L. M., PINIÉS P., and NEWMAN P. A Variational Approach to Online Road and Path Segmentation with Monocular Vision. Proceedings of the IEEE International Conference on Robotics and Automation, Seattle, Washington, 2015, pp. 1633-1639. https://doi.org/10.1109/ICRA.2015.7139407

[15] LIEB D., LOOKINGBILL A., and THRUN S. Adaptive road following using self-supervised learning and reverse optical flow. *Robotics: Science and Systems,* 2005, 1: 273–280. https://doi.org/10.15607/rss.2005.i.036

[16] TAN C., HONG T., CHANG T., and SHNEIER M. Color model-based real-time learning for road following. Proceedings of the IEEE Intelligent Transportation Systems Conference, Toronto, 2006, pp. 939-944. https://doi.org/10.1109/ITSC.2006.1706865

[17] WANG Z., BOVIK A. C., SHEIKH H. R., and SIMONCELL E. P. Image Quality Assessment: From Error Visibility to Structural Similarity. *IEEE Transaction on Image Processing,* 2004, 13(4): 600-612. https://doi.org/10.1109/TIP.2003.819861

[18] YANHUI W., CHUAN Y., and YUHONG D. Multi-scale Extraction of Road Network Incremental Information

in Navigation Electronic Map. *Journal of Southwest Jiaotong University*, 2015, 50(4). http://jsju.org/index.php/journal/article/view/154

参考文:

[1] SOMAWIRATA I. K. 和 UTAMININGRUM F. 基于色彩空间和聚类连接的道路检测。 2016 年北京国际信号与图像处理会议论文集，第 118-122 页。https://doi.org/10.1109/SIPROCESS.2016.7888235

[2] FRITSCH J.，KUHNL T. 和 GEIGER A。道路检测算法的新性能衡量和评估基准。电气工程师学会国际智能交通系统会议论文集，海牙，2013，第 1693-1700 页。https://doi.org/10.1109/ITSC.2013.6728473

[3] KONG H.，AUDIBERT J.-Y. 和 PONCE J. 用于道路检测的消失点检测。电气工程师学会计算机视觉和模式识别会议论文集，佛罗里达州迈阿密，2009，第 96-103 页。 https://doi.org/10.1109/CVPR.2009.5206787

[4] 丁伟，李 LI。复杂城市道路环境中的有效消失点检测方法。IET 计算机视觉，2015，9（4）：549-558。https://doi.org/10.1049/iet-cvi.2014.0187

[5] WEILI D.， YONG L.， WENFENG W.， YUANUANUAN Z. 基于垂直和平行线包络的城市道路图像消失点检测算法。光学学报，2014，34（10）：1015002. https://doi.org/10.3788/AOS201434.1015002

[6] KONG H.，AUDIBERT J.-Y. 和 PONCE J. 从单个图像进行一般道路检测。电气工程师学会图像处理事务，2010，19（8）：2211-222。https://doi.org/10.1109/TIP.2010.2045715

[7] 郑涛，程旭，潮明，等。基于消失点和主方向估计的道路分割。计算机研究与发展，2014，51（4）：762-772。

[8] 肖琳 L.，俞峰 J.，严 G.，小雪 F.和魏兴 L.基于区域增长的非结构化道路检测。电气工程师学会第 30 届中国控制与决策会议论文集，沉阳，2018，第 3451-3456 页。 https://doi.org/10.1109/CCDC.2018.8407720

[9] YAO J.，RAMALINGAM S.，TAGUCHI Y.，MIKI Y. 和 URTASUN R. 从单眼视频估计可驾驶的无碰撞空间。电气工程师学会冬季计算机视觉应用大会会议论文集，夏威夷，唯客乐，2015，第 420-427 页。https://doi.org/10.1109/WACV.2015.62

[10] LEVI D.， GARNETT N.， FETAYA E. 和 HERZLYIA I. Stixelnet：用于障碍物检测和道路分割的深层卷积网络。英国机器视觉会议论文集，斯旺西，2015，第 109.1-109.12 页。https://dx.doi.org/10.5244/C.29.109

[11] MOHAN R. 用于场景解析的深度反卷积网络，2014 年。https：//arxiv.org/pdf/1411.4101.pdf

[12] CHENG H.-Y.，JENG B.-S.，TSENG P.-T. 和 FAN K.-C.在交通场景中移动车辆的车道检测。电气工程师学会智能交通系统交易，2006，7（4）：571-582。https://doi.org/10.1109/TITS.2006.883940

[13] AL-ABAID S. A. F. 使用图像处理的智能交通控制系统：评论。西南交通大学学报，2020，55（1）。https://doi.org/10.35741/issn.0258-2724.55.1.31

[14] PAZ L. M.，PINIÉSP. 和 NEWMAN P. 一种具有单目视觉的在线道路和路径分割方法。电气工程师学会机器人与自动化国际会议论文集，华盛顿州西雅图，2015，第 1633-1639 页。https://doi.org/10.1109/ICRA.2015.7139407

[15] LIEB D.，LOOKINGBILL A. 和 THRUN S. 使用自监督学习和反向光流的自适应道路跟踪。机器人技术：科学与系统，2005，1：273-280。https://doi.org/10.15607/rss.2005.i.036

[16] TAN C.，HONG T.，CHANT T. 和 SHNEIER M. 基于颜色模型的道路跟踪实时学习。电气工程师学会智能交通系统会议论文集，多伦多，2006，第 939-944 页。https://doi.org/10.1109/ITSC.2006.1706865

[17] WANG Z.， BOVIK A. C.， SHEIKH H. R. 和 SIMONCELL E. P. 图像质量评估：从错误可见性到结构相似性。电气工程师学会图像处理事务，2004，13（4）：600-612。 https://doi.org/10.1109/TIP.2003.819861

[18] 闫辉 W.，CHEN Y. 和 YUHONG D. 导航电子地图中路网增量信息的多尺度提取。西南交通大学学报，2015，50（4）。http://jsju.org/index.php/journal/article/view/154