Recognition of Road Markings from In-Vehicle Camera Images by a Generative Learning Method

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Abstract

In this paper, we propose a method for recognition of road markings from in-vehicle camera images. A road marking in in-vehicle camera images has a variety of appearance due to the change of position and distance between the camera and the road marking, blur effect, and so on. Therefore, accurate recognition of road markings becomes difficult in real environment. Our method generates numerous learning images with the appearance variation in order to recognize road markings in real environment accurately. The effectiveness of the proposed method was confirmed through a recognition experiment using actual in-vehicle camera images.

1 Introduction

With the development in ITS technology, recognition of traffic circumstances by using an in-vehicle camera has attracted a great deal of attention. This enables safety driving, making and updating traffic maps, and so on. In this paper, we propose a method for recognition of road markings from in-vehicle camera images (Figure 1 left). Road markings are painted on the road-plane, which indicate driving directions warnings and so on. Therefore, their recognition is helpful to understand the traffic environment. Li et al. [1] use contour to recognize road markings. The recognition accuracy, however, degrades where a major change of appearance occurs due to change of position and distance between the camera and a road marking, and optical and motion blurring. In our work, we aim at realizing a more robust recognition method by considering such appearance changes caused by such degradation factors.

In this paper, we propose a method that uses an appearance-based approach, which directly learns road marking images with appearance changes. The problem of the appearance-based method is that the cost to collect learning images is very expensive. In order to reduce the cost, a generative learning method for the recognition of traffic signs has been proposed by Ishida et al. [2] [3], which generates learning images. The method constructs generation models considering factors that cause appearance changes so that the generated images should be simulated as close as possible to images captured from the real-world. Such an approach is known as a kind of a virtual learning method [4].

It is important that the generation models reflect accurately real-world factors of appearance changes. Therefore, we tried to construct generation models for road markings considering appearance changes which occur in actual driving environments. It is also important to provide the models with appropriate generation parameters to generate realistic learning images, we determined the generation parameters by analyzing actual driving data.

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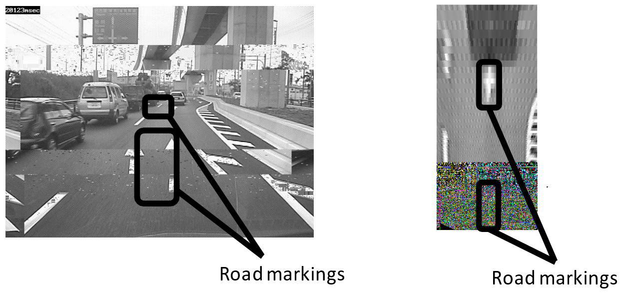

Figure 1: Road markings in an in-vehicle camera image (left) and road markings transformed to the road-plane image (right).

The paper is organized as follows: The proposed method is introduced in Section 2. Section 3 shows the results of recognition experiments using actual in-vehicle camera images and confirms the effectiveness of our method. Finally, Section 4 concludes the paper.

2 Recognition of road markings by a generative learning method

2.1 Overview

Assuming a road plane is flat, a projection transformation using a projection matrix $\mathbf{M}$ is applied to an in-vehicle camera image to obtain a road-plane image which is an image of the road viewed from directly above (Figure 1 right). In the road-plane image, road markings are represented in the same size regardless to the distance from the camera. This transformation simplifies the following operations of the method. The projection matrix $\mathbf{M}$ is calculated from the relation between the position and posture of the camera and a road marking. The parameters that represent the relation between the camera and a road marking are as follows:

- Position of the camera: $\mathbf{p} = (d, l, h)$
  - Distance in the running direction: d [m]
  - Side gap to the running position: l [m]
  - Height from the road plane: h [m]
- Posture of the camera: $\mathbf{r} = (\theta\ [°], \phi\ [°], \psi\ [°])$

Figure 2 illustrates these geometrical parameters.

Table 3: Comparison of recognition rates.

Method	Overall		10m–20m		20m–30m		30m–40m	
Proposed	**0.95**	**(949/1000)**	**0.97**	**(485/500)**	**0.94**	**(281/300)**	**0.87**	**(173/200)**
NCC	0.85	(847/1000)	0.88	(440/500)	0.53	(256/300)	0.76	(151/200)
Twice SD	0.91	(912/1000)	0.95	(477/500)	0.92	(276/300)	0.80	(159/200)
Half SD	0.93	(932/1000)	0.96	(479/500)	0.94	(283/300)	0.85	(170/200)

Table 2: Generation parameters (normal distribution).

Parameter	Average		Standard deviation	
h	1.6	m	0.01	m
l	-0.2	m	3.0	m
θ	0.0	°	3.03	°
ϕ	0.0	°	0.64	°
ψ	0.0	°	0.57	°
Δd	5.24	m/s	3/86	m/s
Δh	0.0	m/s	0.01	m/s
Δl	0.0	m/s	0.1	m/s
$\Delta\theta$	0.69	°/s	1.36	°/s
$\Delta\phi$	0.30	°/s	0.38	°/s
$\Delta\psi$	0.30	°/s	0.29	°/s
Δx	0.0	pixel	1.0	pixel
Δy	0.0	pixel	0.3	pixel
Δs_x	0.0	pixel	2.0	pixel
Δs_y	0.0	pixel	0.6	pixel

Figure 9: Road marking classes

were the five shown in Figure 9. We created each subspace from $N = 500$ learning images, with a dimension of $L = 11$, which was determined based on the result of a preliminary experiment. Table 1 shows the generation parameters, while Table 2 shows the mean values and the standard deviations of the distribution of the generation parameters.

The proposed method and the following three comparative methods were applied to 1,000 actual in-vehicle camera images.

- Comparative method 1 (NCC) :
  The normalized correlation between an input image and the original image of each class was used as the similarity.

- Comparative method 2 (Twice SD):
  Twice the values of the standard deviations (SD) for $h, l, \theta, \phi, \psi, \Delta d, \Delta h, \Delta l, \Delta\theta, \Delta\phi, \Delta\psi$ shown in Table 2 were used to generate the learning images.

- Comparative method 3 (Half SD) :
  Half the values of the standard deviations (SD) for $h, l, \theta, \phi, \psi, \Delta d, \Delta h, \Delta l, \Delta\theta, \Delta\phi, \Delta\psi$ were used.

3.2 Results and Discussion

Table 3 shows the overall recognition rate and the recognition rates for each group. The rates are divided into three groups according to the distance to the road markings for analysis purpose.

Since the recognition rates of our method ware higher than the comparative methods, we confirmed that it is effective for road marking recognition. Compared with the comparative method 1 (NCC), the recognition rate improved especially when road markings were distant. This demonstrates that the proposed method keeps a relatively high recognition performance even if the appearances of a road marking changes significantly. Since the recognition rate of the proposed method was higher than those of the comparative methods 2 (Twice SD) and 3 (Half SD), we can see that the recognition rates improved by using adequate settings of generation parameters.

4 Conclusion

In this paper, we proposed a method for recognizing road markings from in-vehicle camera images. The proposed method generates learning images using generation models considering appearance changes of road markings, and thus could achieve robust recognition of road markings in actual traffic environments. We confirmed the effectiveness of the proposed method from the results of an experiment using actual in-vehicle camera images. Future works include development of generation models considering other factors, such as flaking and partial occlusions of road markings.

Acknowledgments

The authors would like to thank their colleagues for useful discussions. Parts of this research were supported by the Grant-In-Aid for Scientific Research from the Japan Society for Promotion of Science.

References

[1] Y. Li, K. He, and Peifa Jia, "Road Markers Recognition Based on Shape Information", Proc. 2007 IEEE Intelligent Vehicles Sympo., pp.117–122, Istanbul, Turkey, Jun. 2007.

[2] H. Ishida, T. Takahashi, I. Ide, Y. Mekada, and H. Murase, "Identification of Degraded Traffic Sign Symbols by a Generative Learning Method", Proc. Int. Conf. on Pattern Recognition 2006, Vol.1, pp.531–534, Hongkong, Aug. 2006.

[3] H. Ishida, T. Takahashi, I. Ide, Y. Mekada, and H. Murase,"Generation of Training Data by Degradation Models for Traffic Sign Symbol Recognition", IEICE Trans., Vol.E90-D, No.8, pp.1134–1141, Aug. 2007.

[4] T. Amano, A. Yamaguchi, and S. Inokuchi, "Eigenspace Approach for Object Recognition and its Pose Detection", Systems and Computers in Japan, John Wiley & Sons,Inc., Vol.31, No.11, pp.60–69, Nov. 2000.

[5] B. Okumura, M. Kanbara, and N. Yokoya, "Augmented Reality Based on Estimation of Defocusing and Motion Blurring from Captured Images", Proc. IEEE/ACM Int. Symp. on Mixed and Augmented Reality, pp.97–106, Santa Barbara USA, Oct. 2002.