Lane-level Positioning based on 3D Tracking Path of Traffic Signs

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Keywords: Lane-level Vehicle Positioning, Ego-lane Detection, ADAS, Autonomous Driving, Driver Assistant, SVM, Stereo Matching, Traffic Sign Detection.

Abstract: Lane-level vehicle positioning is an important task for enhancing the accuracy of in-vehicle navigation systems and the safety of autonomous vehicles. GPS (Global Positioning System) or DGPS (Differential GPS) techniques are generally used in lane-level poisoning systems, which only provide an accuracy level up to 2-3 m. In this paper, we introduce a vision based lane-level positioning technique that provides more accurate prediction results. The proposed method predicts the current driving lane of the vehicle by tracking the 3D location of the traffic signs that are in the side-way of the road using a stereo camera. Several experiments are conducted to analyse the feasibility of the proposed method in driving lane level prediction. According to the experimental results, the proposed method could achieve 90.9% accuracy.

1 INTRODUCTION

Lane-level positioning is a technique that finds the index of the driving lane of a vehicle. It is an important technique in the field of autonomous driving and Advanced Driver Assistant Systems (ADAS). Knowing the position of a vehicle with the lane-level accuracy, advanced navigation services can be provided. For example, a current in-vehicle navigation platform provides simple directions to the destination. Due to the limited accuracy of the GPS signal, the current navigation platform provides only the road-level position of the vehicle. By the way, if there is a technique of lane-level positioning, more advanced services can be provided. For example, the navigation platform knows in which lane the vehicle is driving. If the vehicle is not in the correct lane of the direction, the platform can provide a warning signal to the driver and suggest a correct lane. Another service can be applied to an autonomous driving system. By knowing the lane-level position of the vehicle, the autonomous driving system can drive the vehicle to the correct lane for the destination.

In the previous work, various techniques have been employed for lane-level positioning. There are promising systems that predict the lane-level position by obtaining the location of the driving car using expensive high-precision GPS and digital map information(Du et al., 2004; Du and Barth, 2008). Techniques based on wireless network communication between vehicles are also used to determine the lane-level position(Dao et al., 2007). In (Kühnl et al., 2012; Kuhnl et al., 2013), the authors proposed a lane-level positioning technique, which extract SPRAY(SPatial RAY) features at lane marking and classify the driving lane with GentleBoost. However, the accuracy is approximately 15 m for GPS-based systems and 2-3 m for DGPS-based systems, which is not enough for predicting the vehicle position in lane-level. Furthermore, the systems based on vehicle to vehicle communication networks require partner vehicles and will

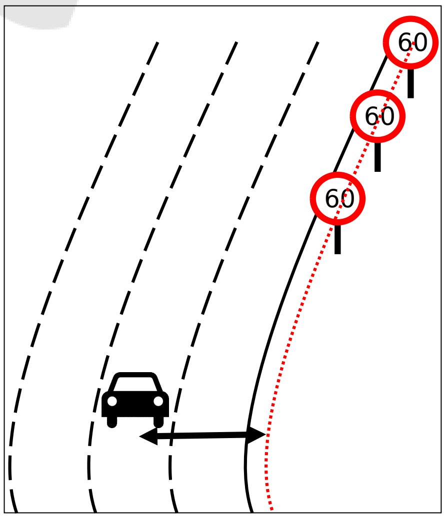

Figure 1: Lane-level vehicle positioning using path of traffic signs.

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not work accurately in rural areas.

Therefore, this paper proposes a more accurate and standalone method offering promising result using stereo vision techniques. The proposed method utilizes the 3D information of the traffic signs, which are tracked by a stereo camera. Traffic sign detection, stereo matching, and lane-level positioning are the three main stages of the proposed method. Section 2 first gives an overview of the proposed method and then provides a detail explanation of each stage; traffic sign detection, tracking, stereo matching, and lane-level positioning. Experimental results are described in Section 3, and the conclusions and future works are included in Section 4.

Figure 3: Generating path of traffic signs with detection, tracking and calculation 3D location of it.

2 LANE-LEVEL POSITIONING

In this paper, we present a lane-level positioning method using a stereo camera. Most of the traffic signs are located between the side-way and the driving lane as in Figure 1. We can use the information on traffic sign locations to determine the current lane of the vehicle. The system consists of four main stages; traffic sign detection, tracking, stereo matching and lane-level positioning (Figure 2).

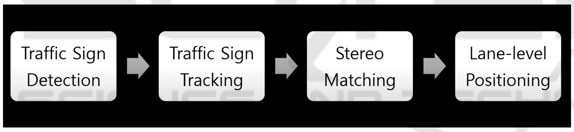


Figure 2: Flow chart of the proposed vehicle lane-level positioning system.

2.1 Traffic Sign Detection

The proposed system determines the lane-level position using 3D path of the traffic signs. Therefore, the first step of the proposed system is detecting traffic sign. The traffic sign detection process consists of two parts; detecting the traffic sign candidates and classification using machine learning.

Detecting traffic signs by searching through the whole image is very time-consuming. Therefore, in the proposed method, we first extract few convincing traffic sign candidates from the input image. There are promising methods, which can be used to extract the traffic sign candidates, such as binarization with red color (Maldonado-Bascón et al., 2007; Bahlmann et al., 2005; De La Escalera et al., 1997) and using geometrical features of the traffic signs (Bahlmann et al., 2005; Garcia-Garrido et al., 2006; García-Garrido et al., 2005). In this papers, binarization with red color used to define traffic sign candidates. To detect the red boundary of the traffic signs, we first converted the input images to HSV (Hue, Saturation, Value) color space and defined appropriate threshold values for each channel. Then these threshold values are used to make a binary image by applying thresholding. A connected component labeling method is used to connect the red pixels and generate clusters.

However, not all clusters are the traffic sign. The clusters are the candidates of the traffic sign. To determine the traffic sign, machine learning methods which like neural network or SVM are generally used(Maldonado-Bascón et al., 2007; Bahlmann et al., 2005; De La Escalera et al., 1997; Garcia-Garrido et al., 2006; García-Garrido et al., 2005). Deep learning technique which as neural network based methods are popular recently but the deep learning technique needs tons of images as 10 thousand or more. However, this paper detects traffic signs in Korea, and there is no open traffic sign database. Hence, it is hard to obtain enough amount of traffic sign images to apply deep learning technique. General backpropagation algorithm in neural network method also easily fall in local minima, when there doesn't exist enough amount of training data. However, SVM always finds global minima (Antkowiak, 2006; Burges, 1998). Therefore, proposed system uses SVM.

Figure 4: Binarization with red color.

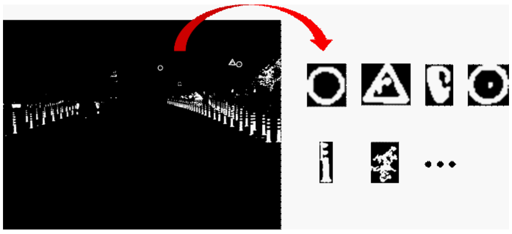


Figure 5: Extract candidates in binarization image.

Abovementioned, there is no open traffic sign database in Korea. Therefore, the used database was formed with our lab. Traffic signs are consist of 3 types geometrically; circle, triangle, invert triangle. If putting the 3 types of traffic sign to one positive class, then it's hard to find hyperplane which have maximal margin between positive and negative classes because variation of the boundary of traffic sign is too large. Therefore, to train SVM appropriate, we designed 3 positive classes; circle, triangle, invert triangle classes $\{Class_{circle}, Class_{triangle}, Class_{invtriangle}\}$. Multi-classification method, 'one versus all', are used to determine traffic sign. Eventually, traffic sign detection SVM is trained with positive 3 class $\{Class_{circle}, Class_{triangle}, Class_{invtriangle}\}$ and negative class $\{Class_{negative}\}$.

Training SVM with known features gives better performance than training with vectorized original RGB image only. The proposed training method of traffic sign detection extracts 5 features at the traffic sign image and concatenate those features to create a single feature vector. First, original traffic sign image is resized to 50×50 pixel. Applying sobel operator with three directions, horizontal, vertical, diagonal, generates 3 edge value feature image. Extracting red color at traffic sign image generates one binary feature image. The last feature is intensity feature image. After extracting 5 features at traffic sign image, vectorizing each feature image and concatenating the vectorized feature makes $50 \times 50 \times 5$ dimensional feature. The proposed SVM training technique is trained

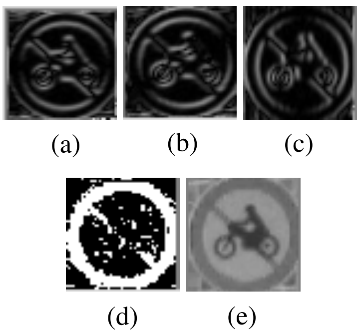


Figure 6: Used 5 features. (a) diagonal edge feature, (b) horizontal edge feature, (c) vertical edge feature, (d) red channel feature, (e) intensity feature.

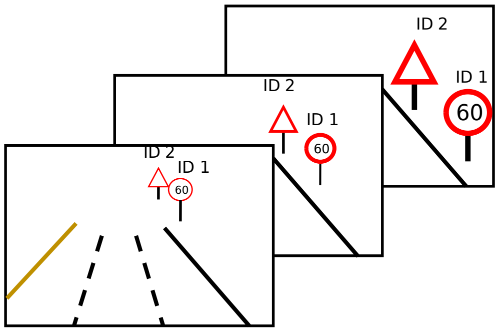


Figure 7: Tracking traffic sign ID in sequence of frames.

with this $50 \times 50 \times 5$ dimensional feature.

Eventually, The proposed traffic sign detection SVM is trained with circle, triangle, invert triangle, negative classes, $\{Class_{circle}, Class_{triangle}, Class_{invtriangle}, Class_{negative}\}$. Each classes are classified with multi-classification method named 'one versus all' method.

2.2 Tracking Traffic Sign

The path of the traffic sign is used to determine the lane-level position. In order to create the path, the system should track the traffic sign and also calculate 3D location of the traffic sign. Therefore, the system tracks the traffic sign in image frame sequence. To track the traffic sign, template matching based tracking is used. If the system detects new traffic sign in the frame, the system gives identification number to it. If the system detects already detected traffic sign which detected in the previous frame, the system gives same identification number to it. Template matching between traffic signs which in previous five frames and traffic sign in the current frame makes same traffic sign have the same identification number.

2.3 Stereo Matching

To find locations of the traffic signs in 3D space, we use stereo matching not between whole left image and whole right image but only between left traffic sign and right traffic sign.

The system detects traffic sign only in left image.

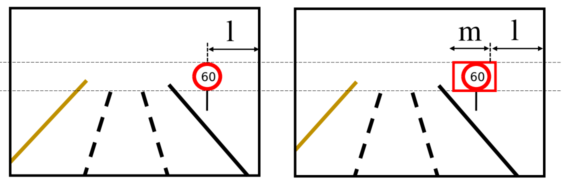


Figure 8: Stereo images. l indicates center of traffic sign in left. m indicates max disparity. Red rectangle shows search range for stereo matching.

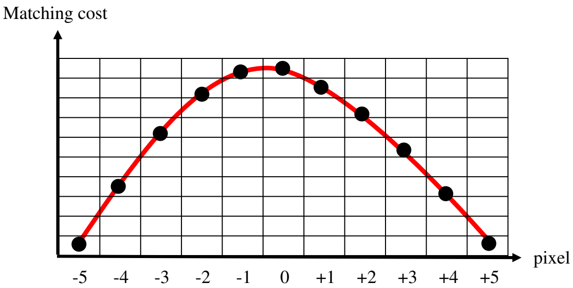


Figure 9: Find exact matching pixel as subpixel using least square method.

But, to calculate 3D location, the location of the traffic sign in the right image should be determined, so left detected traffic sign image is used to detect traffic sign is right image.

To find corresponding traffic sign in the right image, setting ROI (Region Of Interest) in the right image is efficient. For stereo matching, the stereo images should be rectified first because rectification makes two stereo images locate to a common image plane. With rectification, traffic signs in the left image and right image have the same height, so it can limit height of ROI. The max disparity can limit the width of ROI. With above two constraints, Traffic sign detection ROI in the right image is determined.

To find corresponding traffic sign in the right image, template matching with matching cost NCC (Normalized Cross Correlation) is used. Maximum NCC value point is corresponding point. However, this corresponding point is pixel scale value. To more accurate calculation, left 5 point of corresponding point, right 5 point of corresponding point and corresponding point, total 11 points are used to calculate subpixel corresponding point. To find most corresponding point in subpixel, quadratic function which fit with 11 point is calculated and most corresponding point is found at point of inflection.

The 3D coordinate of the traffic sign is finally calculated with triangulation with detected traffic sign in the left image and corresponding traffic sign in right image. With 3D coordinate of traffic sign and tracking in the sequence of frames, the path of traffic signs can be measured.

2.4 Lane-level Vehicle Positioning

Main idea of this paper is to find current lane-level position. Now, the system knows the 3D coordinates of the traffic sign not only current frame but also previous frames. So, the path of traffic signs can be determined. When traffic sign is captured a scene of frames, 5 to 15 traffic sign is captured at one scene, so curve fitting with these points is needed. To fit the curve on those traffic signs, projection on XZ plane is applied. locations of the traffic signs is now on the XZ plane, so the path of traffic signs is determined with applying least square method with those traffic sign points. Interception of x-axis is distance between driving car and side-way. Proposed system finds driving car's its own lane-level using with width of lane. Using width of lane and the distance between driving car and side-way identify current lane-level position.

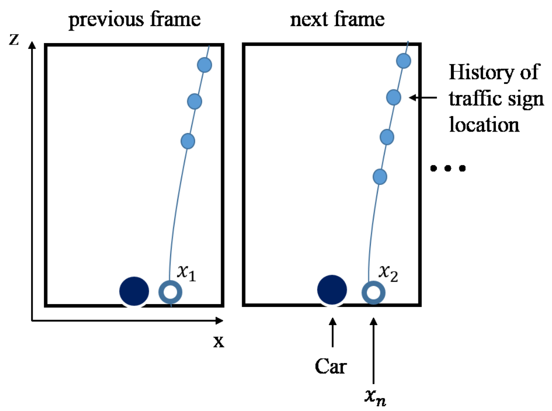


Figure 10: 3D tracking path of traffic signs. x_n indicates interception of x-axis of quadratic function which is determine with 3D tracking path of traffic signs.

Coordinate of interception of x-axis indicates distance between the car and side-way but distance are determined not just one interception but weighted sum of interceptions that are made with sequence of frames. Equation of weighted sum is shown below equation (1). n indicates number of the interceptions. x_n indicates the interception.

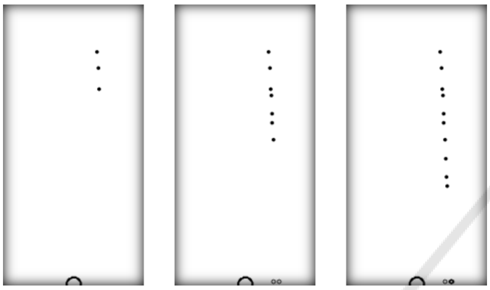
$$D = \frac{n^2 x_n + (n-1)^2 x_{n-1} + \cdots + 1^2 x_1}{n^2 + (n-1)^2 + \cdots + 1^2} \quad (1)$$

Driving lane is generally count from left to right, so dividing distance between driving car and side-way by lane width is not correct because this is count from right to left. Therefore, Total lane is used to re-index to left to right counting. Also, there are some gap between road and side-way, so it should be consider when calculate the real distance.

W is width of lane. With the W, current lane-level position can be measured. Calculating lane-level can solved with equation (2). L indicates the total lane of driving direction and W indicates lanes width and x_n indicates the distance between the driving car and side-way and α indicates gap which between road and side-way.

$$Driving \quad lane = L - \left\lfloor \frac{L \times W}{D - \alpha} \right\rfloor \quad (2)$$

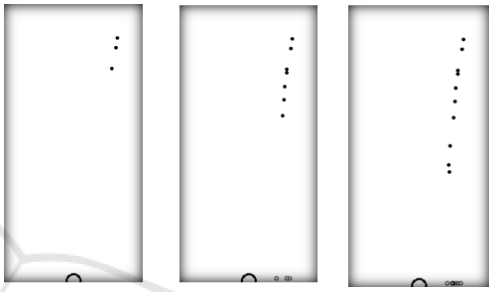
(a)



(b)

Figure 11: Result image of straight road. (a)shows result image. (b) shows 3D tracking position of traffic sign.

(a)



(b)

Figure 12: Result image of curved road. (a) shows curved road. (b) shows 3D tracking position of traffic sign.

Figure 13: Result image of lane-level positioning.

3 EXPERIMENTS

BumbleBee Xbee3 is used to capture the stereo images. The camera was mounted on the front windscreen of the car. The experiment data was captured on typical roads in Korea.

For traffic sign detection, abovementioned SVM is trained with 4 classes, $\{Class_{circle}, Class_{triangle}, Class_{invtriangle}, Class_{negative}\}$, which include 402 circle data, 229 triangle data, 156 invert triangle data, and 1,164 negative data. The detection performance is shown in table 2.

Table 1: Training data of traffic sign detection SVM.

Circle	Triangle	Invert tringale	Negative
402	229	156	1,164

Table 2: Performance of detection Traffic sign. TP: True Positive, FP: False Positive, FN: False Negative.

TP	FP	FN	Precision	Recall
1,754	51	2,061	0.9717	0.8510

The distance between the driving lane and the side-way is measured by the interceptions of the x-axis, which is calculated frame by frame. However, the system does not use the interception for calculating the distance, if the number of traffic sign history points is less than five. If we generate a curve using only 3 or 4 points of the traffic sign path, that curve may contain large error especially in the case of straight lanes. A curve generated using 5 points is

Table 3: Result of lane-level positioning.

Scene	Total number of lanes	Ground truth lane	Detected lane position	Measured distance (m)
1	2	1	1	2.42
2	2	2	2	3.46
3	2	1	1	5.66
4	2	2	2	4.01
5	2	2	2	4.28
6	2	1	1	6.95
7	2	1	1	7.75
8	2	2	2	4.31
9	2	2	2	3.77
10	2	2	2	3.69
11	3	3	3	3.48
12	2	2	2	3.35
13	2	2	2	3.52
14	4	3	4(Fail)	1.64
15	3	2	2	5.65
16	3	2	2	5.91
17	3	2	2	5.52
18	2	1	1	9.09
19	2	1	1	6.64
20	2	1	1	6.95
21	2	2	2	4.14
22	3	1	3(Fail)	1.27

Table 4: Result of vehicle lane-level positioning.

Number of scene	Correct	Fail	Accuracy
22	20	2	90.9%

almost a straight line; therefore, we use the interception for calculating the distance only if there are more than four history points. Frame by frame ground truth driving lane is determined by human inception. Figure 11 and figure 13 show sequences of traffic sign tracking frames, which is related to a straight lane and a curved lane respectively.

There are special parameters, α and L, to solve in equation (2). According to the standards in Korea, the lanes width is about 3 m to 3.5 m, and it is wide enough to permit some amount of error of measurements. As the most of the roads have less than six lanes, α was set to 1.0 m in our experiments. L can be identified from lane detection process or industrial map API using GPS, however in this experiment, L is determined by the ground truth data.

4 CONCLUSIONS

Autonomous driving needs not only the global position and the relative position between vehicles but also the lane-level position. Very few research works have been done on lane-level positioning using vision based approach so far. This paper proposed a new computer vision based approach of predicting lane-level position using traffic sign tracking. The performance of the system is 90.9% of accuracy.

As future works, we are planning to collect more experiment data in different environmental conditions to analyze the robustness of the proposed system. Furthermore, we can integrate the proposed method with existing lane detection methods to improve the accuracy and the robustness of the lane-level positioning.

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