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Support Vector Machines For Understanding Lane Color and Sidewalks

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***Abstract*—** Understanding road features such as lanes, the color of lanes, and sidewalks in a live video captured from a moving vehicle is essential to build video-based navigation systems. In this paper, we present a novel idea to understand the road features using support vector machines. Various feature vectors including color components of road markings and the difference between two regions, i.e., chosen AOIs, and so on are fed into SVM, deciding colors of lanes and sidewalks robustly. Experimental results are provided to show the robustness of the proposed idea.
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Keywords— video-based navigation system, lane detection, SVMs, autonomous vehicles

I. INTRODUCTION

Recently, many research efforts have been focused on the development of video-based car navigation systems (CNS) to support more realistic navigation functions than traditional map-based CNS. For video-based navigation systems, recognizing lanes in a video sequence captured from a moving vehicle is essential [1]-[2]. Many research efforts have been reported to recognize anes by using edge, color, deformable templates, GPS, and so on [3]-[5]. However, few researches have been reported to recognize the color of lanes for various lighting conditions including shadow, backlight, sunset, and so on. Recognizing the color of lanes is important to decide the lane number in which the car is driving. For instance, if the color of lanes on the left side is yellow, it means the car is driving on the leftmost lane. In this paper, we present a novel idea to recognize lane colors by using support vector machines (SVM). In addition, a novel approach is presented to decide whether or not there are sidewalks on the right side of the road using SVM. An overview and detailed implementation of the proposed SVM are described in Section II. Exhaustive experimental results and conclusions are given in Section III and IV,.

II. Understanding Road Features Using SVM

A. Overview of SVM

SVM is widely used for many pattern recognition problems including face recognition, 3-D object recognition, and so on [6]-[8]. SVM is a statistical learning theory, which uses training data as inputs to generate a decision function as an output to classify unknown data. Suppose there are N training data $\mathbf{x}_i \in R^n$, i=1,2,…, N, where each of data belongs to one of the two classes labeled $y_i \in \{-1,1\}$. As a decision function to classify input data, SVM finds a hyperplane separating two classes with maximum distance from the hyperplane to support vectors. Support vectors are data points from both classes located closest to the separating hyperplane. SVM supports both linearly separable data and linearly non-separable data. If data is separable linearly, SVM finds the following hyperplane using Lagrangian multiplier approach:

$$f(x) = \sum_{i=1}^{N_s} \alpha_i y_i x_i \cdot \mathrm{x} + b , \qquad (1)$$

where N_s is the number of support vectors. To classify input data, the sign of (1) is used. In addition, SVM can be extended to handle data which is not separable linearly using kernel functions. (Please see [6] for details.)

B. The architecture of the proposed SVM

In the proposed approach, SVM is used to decide lane color and the existence of sidewalks, making possible to know lane number on which the car is driving. Fig. 1 shows the block diagram of the proposed SVM-based lane color and sidewalk recognition system.

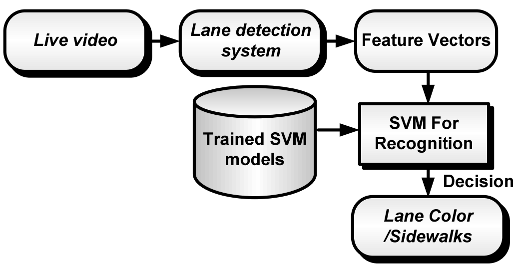

Fig. 1. A block diagram for the proposed SVM-based lane color and sidewalk recognition system

The proposed algorithm starts by detecting lane markings first. Based on the detected position of lane markings, AOIs are chosen, as shown in Fig. 2 and Fig. 3. For lane color recognition, two SVM are trained. One SVM is trained using RGB values of lane markings that are combined into a single feature vector. The other SVM is trained using RGB values of lane markings after reducing illumination effects, as described in Fig. 2.

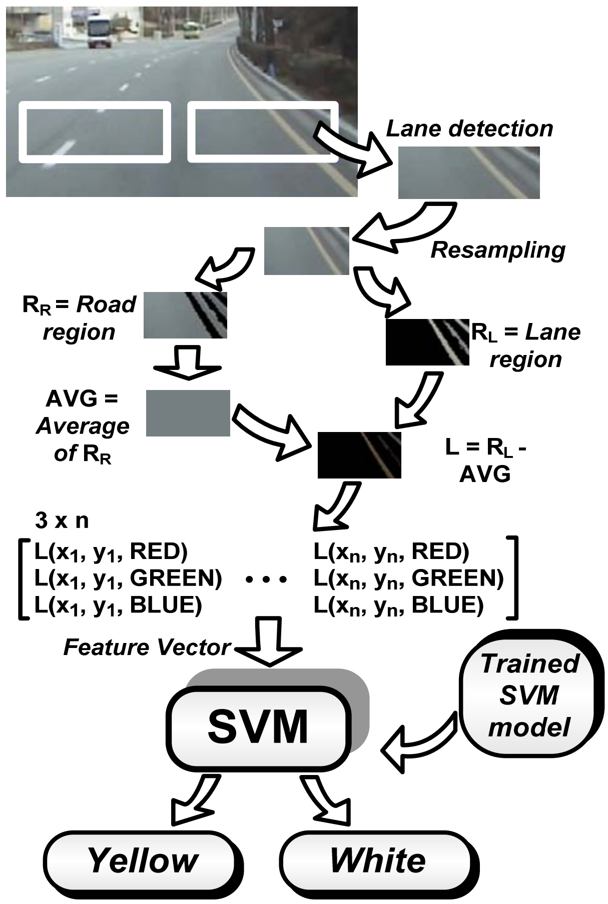

Fig. 2 An example of constructing a feature vector for lane color recognition

To reduce illumination effects, each RGB value of lane markings is subtracted by average RGB values obtained from road region (R_R) that does not contain lane markings, as depicted in Fig. 2.

For detecting sidewalks, Fig. 3 shows how to construct a feature vector for SVM. Three areas chosen from the road (marked as A, B, and C), whose size is 50x50, are obtained and resampled to 25x25 to reduce computational costs. The region A is assumed to be a correct road region once lane markings are detected correctly. In the proposed SVM system, four features are chosen to construct feature vectors to recognize sidewalks. Four features include edge, gray, color, and color difference between chosen two AOIs.

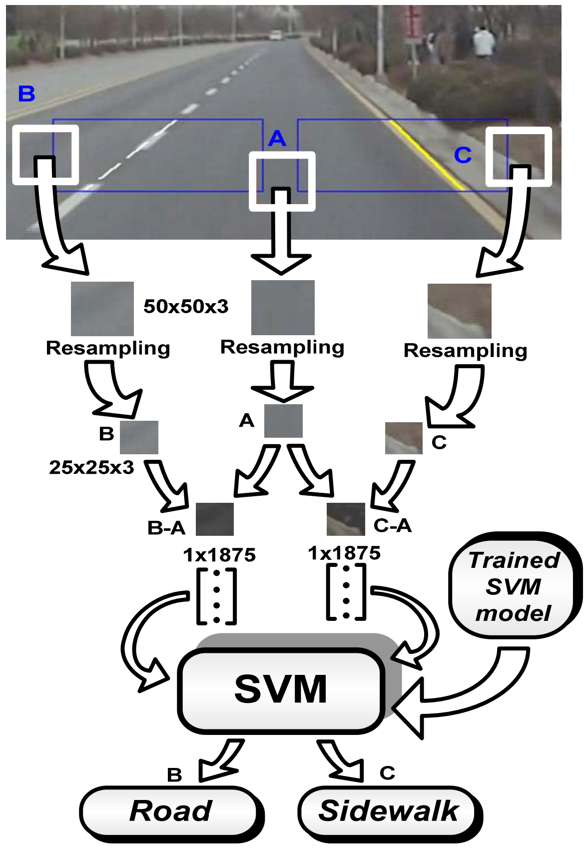

Fig. 3. An example of constructing a feature vector for SVM for the recognition of sidewalks using the difference between center (A) and left(B) (or center (A) and right (C)) AOIs

For instance, to construct feature vectors for the color difference, two difference vectors are obtained, i.e., B-A and C-A, and used as inputs to train and recognize sidewalks. Based on the assumptions that road should have homogeneous color and texture information, the difference B-A should be small if B is taken from the road. If C is taken from sidewalks, the difference vector C-A should be big.

III. Experimental Results

We have tested the proposed idea for a various road and illumination conditions. Video sequences (30 frames/sec) were collected from a moving vehicle, driving around 60km/hour, equipped with GPS and a CCD camera in downtown of Daejeon, Korea. About 49,050 video frames were tested and C++ was used to implement the proposed algorithm in Pentium IV 2 GHz PC.

Table 1 shows the performance of the proposed SVM for lane color recognition. Test frames include various illumination conditions such as shadow, sunset, backlight, tunnel, and so on. The SVM trained by RGB values after reducing illumination effects showed better performance than the RGB-based SVM approach.

Table 1. The performance of SVM for recognizing lane color

SVM-based approach for poorly illuminated test video			
RGB		RGB after reducing illumination effects	
Linear	Radial basis	Linear	Radial basis
70.7%	56.3%	87.8%	70.4%

Figure 4 shows examples of recognized results. Although the proposed SVM-based lane color recognition showd good performances, it still had a difficulty to recognize lane color when threr are string headlingths, street lanp,too dark,and so on.

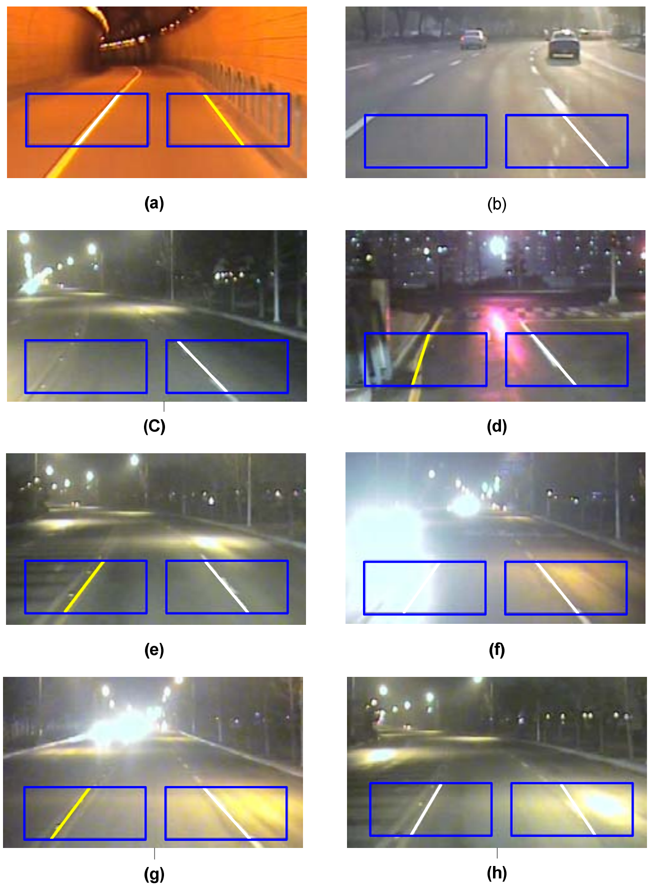

Fig. 4 Example of results for recognizing colors of lane markings for the 3rd group:(a) success in a tunnel; (b) fail to detect the left lane mark due to it's not in AOI; (c) fail to detect the left lane mark due to it is too dark; (d)(e) success via background color removal;(f) fail bacause the head light is so bright; (g)(h) success via background color removal.

To test the performance of recognizing sidewalks using SVM, many test vectors were tested as indicated in Table 2. Edge, gray, color, and the difference (as described in Section II) features were used for test vectors.

Table 2. The performance of SVM for recognizing sidewalks.

Test vector (dimension)	linear	Linear +moving average	Radial basis	Radial basis +moving average
Edge (25x25x3)	87.9%	90.9%	65.0%	68.5%
Gray (25x25)	90.5%	92.3%	68.0%	69.8%
Gray + Edge (25x25x2)	92.5%	95.7%	70.2%	73.2%
RGB (25x25x3)	82.0%	83.2%	60.2%	61.2%
RGB + Edge (25x25x6)	95.0%	97.3%	72.1%	74.4%
Diff. (25x25x3)	83.7%	84.8%	61.3%	62.1%
Diff. + Edge (25x25x6)	95.0%	97.4%	72.8%	74.8%

In addition, edge information were combined with other features for the testing. For instance, "Diff. + Edge" was a test vector consisted of the difference attached by edge data. For kernel functions, linear and radial basis functions were tested and moving average filtering were added to improve the performance in our implementations. Among test vectors, edge combined with the difference showed the best performances, providing 95% for the test video sequences. Fig. 5 shows some of failed results. The proposed approach failed when AOIs contained heterogeneous patterns such as markings(as shown in (a)) or cars(as shown in (b))and so on.

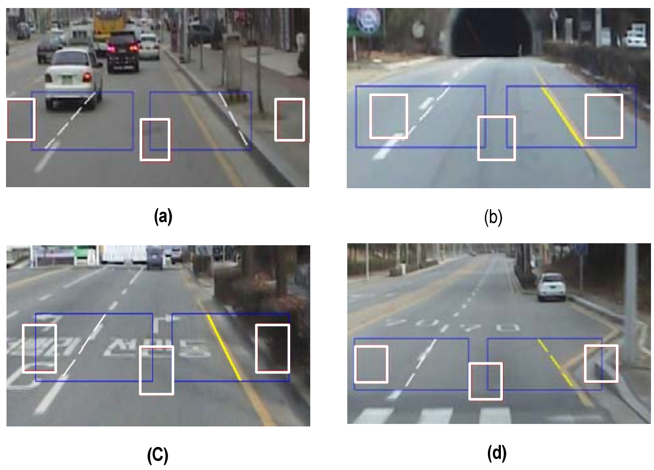

Fig.5 Recognition errors: (a) A left lane mark is blocked by a car and a right lane is unclear; (b)(c) Due to lane markings; (d) A right lane is a curved line.

For lane color and sidewalk recognition, linear SVM outperformed other non-linear kernel functions including radial basis function, and showed promising results for recognizing road features robustly.

IV. Conclusions

In this paper, we have presented a novel idea of using SVM to recognize lane color and sidewalks in a video sequence captured from a moving vehicle. Results from the lane color and sidewalk recognition system can be used to decide whether or not you are driving in the rightmost, middle, or the leftmost lane, allowing us to make more realistic navigation services for video-based navigation systems.

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