HIERARCHICAL LANE DETECTION FOR DIFFERENT TYPES OF ROADS

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ABSTRACT

This paper presents a hierarchical lane detection system with the ability to deal with both structured and unstructured roads. The proposed system classifies the environment first before applying suitable algorithms for different types of roads. For environment classification, pixels with lane-marking colors are extracted as feature points. Eigenvalue Decomposition Regularized Discriminant Analysis is utilized in model selection and maximum likelihood estimation of Gaussian parameters in high dimensional feature space. For structured roads, the extracted feature points are reused for lane detection. For unstructured roads, mean-shift segmentation is applied to divide the scene into regions. Possible road boundary candidates are selected, and Bayes rule is used to choose the most probable boundary pairs. The experimental results show that the system is able to robustly find the boundaries of the lanes on different types of roads and various weather conditions.

Index Terms— *Intelligent systems, Video Analysis, Lane Detection, Machine Vision*

1. INTRODUCTION

Lane detection is a crucial element for developing intelligent vehicles in Advanced Vehicle Control and Safety Systems (AVCSS). Lane boundaries have to be determined accurately in order to warn drivers of lane departure or impending collisions. Lane detection based on machine vision is accomplished by taking images from cameras mounted on the intelligent vehicles. The challenges of lane detection include the ability to deal with various road types, obstacles, passing traffic, shadows, and achieving real-time requirement at the same time. In current literature, researchers often use different strategies to deal with various road types. Edge or intensity based methods [1] are commonly used for structured roads with obvious lane markings because lane markings have clear edges and relatively high intensities. For unstructured roads which have no obvious lane markings or lane boundaries, color and texture information are often employed to distinguish the road surface from the surroundings under the assumption that the color or texture of the road surface is very different from the surroundings beside the road [2].

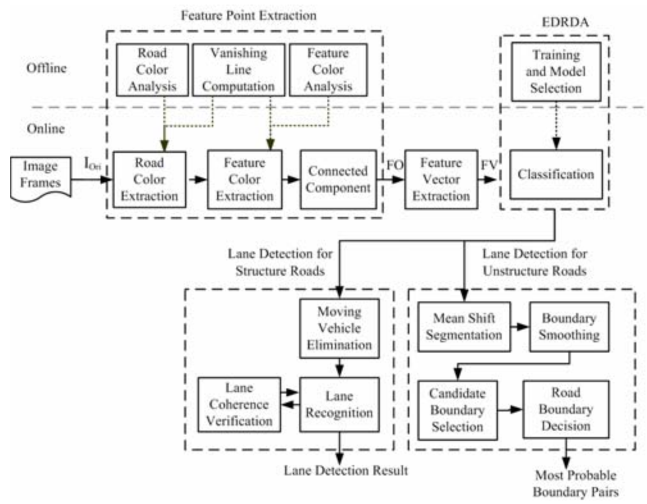

Figure 1. Hierarchical lane detection framework.

An algorithm that performs well on structured roads could work poorly on unstructured roads, whereas an algorithm suitable for handling rural roads might not be suitable for handling highways. More specifically, edge or intensity based methods will fail on unstructured roads due to lack of obvious edges or markings with bright intensities. On the other hand, the assumption for color or texture based methods does not hold for highways because the color and texture of one lane does not have much difference from the lane right next to it. Therefore, the lane boundaries cannot be decided in this way. In this paper, we propose a hierarchical lane detection framework, which is illustrated in Figure 1. The key idea is to classify the current environment into two main categories, structured roads and unstructured roads, automatically and efficiently. Once the classification is done, the system can assign the method that is suitable for the current environment to perform lane detection. We present the environment classification mechanism in Section 2. Lane detection algorithms for structured roads and unstructured roads are described in

Section 3. Experimental results are shown and discussed in Section 4. Finally, we make conclusions in Section 5.

2. ENVIRONMENT CLASSIFICATION

To distinguish structured roads and unstructured roads, feature points are extracted from the scene for classification purpose. Since high dimensional feature vector is formed with extracted feature points, we employ regularization techniques to reduce the misclassification rate. The feature point extraction procedure is explained in sub-section 2.1. Afterwards, model selection, training, and classification mechanisms applied in our work are elaborated in sub-section 2.2.

2.1. Feature Point Extraction

The most distinguishable characteristic between structured roads and unstructured roads is the existence of lane markings. Therefore, we extract the points with the colors of lane markings as the feature points. That is, we define feature colors as colors of lane markings, which can be white, yellow or red. The feature color extraction procedure is based on the color analysis part in our previous work [3]. In order to deal with feature colors in various kinds of illumination conditions, we analyze road colors before feature colors are extracted and enforce the constraint that the detected feature colors should have relatively higher intensities compared to the average intensity of the road surface in the same image frame. Afterwards, a multi-variable Gaussian is employed to represent each of the three main classes of feature colors. The feature extraction procedure will extract lane markings on structured roads. However, it will extract arbitrary clutter regions from unstructured roads. Therefore, by analyzing the feature points we get, we can distinguish these two types of roads.

2.2. Applying EDRDA for Environment Classification

Connected component is performed on the feature points to obtain feature objects. For each feature object with size larger than a threshold, a feature vector is constructed. The feature vector of a feature object includes the x-y coordinates of the center point, the average RGB values, the maximum RGB values, the minimum RGB values, orientation, shape descriptor, width and aspect ratio of the feature object.

Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA) [4] are two very popular parametric classification techniques. In LDA and QDA, the class conditional densities are modeled as Gaussians. To model class conditional densities as Gaussians, we need to estimate the parameters of the Gaussians from the training data. LDA and QDA can perform very well if the parameters are estimated accurately. However, when the dimension of the feature space is high and the number of training samples is small compared to the number of parameters to be estimated, the covariance matrices estimates can become highly variable. For high dimensional data, LDA or QDA often become ill or poorly posed and the misclassification rate will go up dramatically. Therefore, regularization becomes an important issue. The objective of regularization is to reduce variance without adding too much model bias when performing classification.

Friedman [5] proposed a regularization technique, Regularized Discriminant Analysis (RDA), to reduce the variance of the model while introducing little extra bias. However, the selection of the model parameters is not straight-forward and there is no clear interpretation of the model being selected. Bensmail [6] proposes an alternative approach, Eigenvalue Decomposition Regularized Discriminant Analysis (EDRDA), to design regularized classification rules in the Gaussian framework to obtain easier interpreted Gaussian discriminant models and further reduce misclassification rate. The covariance matrix $\sum_k$ for the k^{th} class is re-parameterized in terms of its eigenvalue decomposition $\sum_k = \alpha_k D_k A_k D_k^T$, where $\alpha_k = \left|\sum_k\right|^{1/p}$, D_k is the matrix of eigenvectors of $\sum_k$. A_k is a diagonal matrix such that $|A_k| = 1$ with the normalized eigenvalues of $\sum_k$ on the diagonal in a decreasing order. By allowing some of the parameters α_k, A_k, D_k to vary between classes, (i.e., each parameter can be either the same or different among different classes), eight discriminant models can be obtained. Furthermore, six more models are obtained by modeling the covariance matrix as a diagonal matrix or a scalar multiple of the identity matrix. In total, fourteen models are considered by EDRDA. For each model, the maximum likelihood (M.L.) estimation of the covariance matrix for each class can be computed either in closed form formula or requires iterative procedure. The M.L. estimation equations of the parameters are listed in [6].

At training phases, we perform supervised learning and manually classify the feature objects as left-lane-marking objects (LLM), right-lane-marking objects (RLM), and none-lane-marking objects (NLM). The feature vectors of these objects serve as the training samples for parameter estimation and model selection. The M.L. parameters of the EDRDA models are computed from the training samples. To accelerate the model selection process, only the nine EDRDA models that have closed-form formulas are considered here. Among these EDRDA models, three models with the minimum misclassification rates are selected by cross validation, and their corresponding estimated parameters are used in the classification stage.

At the classification phase, a voting mechanism is utilized to determine the final classification result. The top-three selected EDRDA models are used to perform discriminant analysis on each object. Let n_{iL} denote the number of feature objects classified as LLM with parameter set P_i; n_{iR} and n_{iN} are similarly defined. The number of votes for structured road and unstructured road are

$$vote_{structure} = \sum_{i=1}^{3} w_i n_{iL} + w_i n_{iR}, \quad vote_{unstructure} = \sum_{i=1}^{3} w_i n_{iN}. \quad (1)$$

where w_1, w_2, and w_3 are weights given to models M_1, M_2, and M_3, respectively. The image scene is classified as structured road environment if $vote_{structure}$ is larger than $vote_{unstructure}$ or a threshold.

3. LANE DETECTION

We present the lane detection procedures in the following two subsections.

3.1. Lane Detection for Structured Roads

Since the extracted feature points correspond to lane markings for structured roads, we can utilize these feature points to detect lane boundaries in the subsequent lane detection modules. However, the extracted feature objects include both real lane markings and objects that have similar colors as the lane markings on the road surface. These objects that interfere with lane detection are mainly moving vehicles in the traffic scene. Therefore, to make sure that the lane boundaries can be accurately detected, we need to reduce the influence of these moving vehicles. Taking advantage of the fact that the moving vehicles have different appearances and moving patterns from lane markings on the road surface, the moving vehicle elimination procedure utilizes size, shape, and motion information to distinguish real lane markings from vehicles that have similar colors as the lane markings. Lane recognition module selects the lane boundaries by considering initial angles of inclination and starting points of the lane boundaries first and then search for the turning points for the entire curved lane boundaries. The details could be found in [3].

3.2. Lane Detection for Unstructured Roads

For unstructured roads that do not have obvious lane markings, mean-shift segmentation [7] is employed to divide the entire scene into regions. We assume that road surface and the surroundings beside the road have different colors and texture and therefore will be divided into different regions after segmentation. We also assume that road surfaces belong to relatively homogenous regions. Road boundaries are included in the region boundaries since the road surface and the surroundings belong to different regions after segmentation. Region boundaries are traced by constructing a tree structure and then smoothed to form possible road boundary candidates. We compute the posterior probability that the i^{th} candidate is the left boundary and the j^{th} candidate is the right boundary given the current segmented image frame using Bayes rule.

$$P(L=i, R=j \mid I_{Seg}) = \frac{P(I_{Seg} \mid L=i, R=j) P(L=i, R=j)}{P(I_{Seg})} \quad (2)$$

$P(I_{Seg})$ is constant for every candidate pair and therefore could be ignored. The prior $P(L=i, R=j)$ is computed by considering the starting points and ending points of the candidate pair. If the starting points and the ending points of a candidate pair are impossible to form legitimate road boundaries, the corresponding prior $P(L=i, R=j)$ is set to be zero. For other candidate pairs that have non-zero priors, we set $P(L=i, R=j)$ according to

$$P(L=i, R=j) \propto \frac{1}{dist(S_i, S_L^{k-1}) dist(E_i, E_L^{k-1}) dist(S_j, S_R^{k-1}) dist(E_j, E_R^{k-1})}. \quad (3)$$

where S_i, E_i, S_j, and E_j denote the starting point and ending point of the i^{th} candidate and the j^{th} candidate respectively. S_L^{k-1} and E_L^{k-1} denote the updated starting point and ending point of the *left* road boundary up to time *k-1*. S_R^{k-1} and E_R^{k-1} are similarly defined for the *right* road boundary. A candidate pair has a larger prior if the starting points and the ending points are closer to the previous detection results. For all candidate pairs, the priors are normalized. The likelihood $P(I_{Seg} \mid L=i, R=j)$ is modeled by Gaussian function using the homogeneity of the region H_R between the candidate pairs.

$$P(I_{Seg} \mid L=i, R=j) = e^{-(H_R-1)^2/(2\sigma_H^2)} \quad (4)$$

We select the most probable boundary pairs that maximize $P(L=i, R=j \mid I_{Seg})$ from the candidate boundaries.

4. EXPERIMENTAL RESULTS

In order to verify the effectiveness of the proposed method, we conducted experiments with 12 videos, including both structured-road and unstructured-road environments. The frame rate of the videos is 25 frames per second. In the training and model selection procedure, total 520 feature objects are used as training samples, including 120 LLM feature objects, 100 RLM feature objects, and 300 NLM feature objects. Figure 2 and Figure 3 display the feature points extracted from structured and unstructured-road scenes, respectively. When performing classification, we take a test sample every 10 frames from each video. There are total 5370 frames being classified and only 86 of them are misclassified. Note that the misclassified frames are few enough that the appropriate lane detection algorithm can be selected for each video. For example, we switch from structured lane detection algorithm to unstructured lane detection algorithm only after 10 consecutive frames are classified as unstructured-road environment, and vice versa.

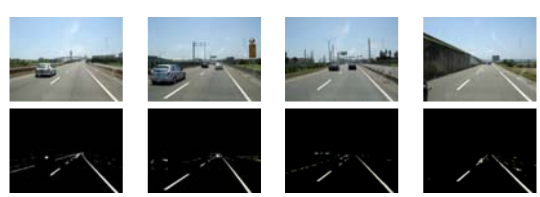

Figure 2. Feature points for structured roads.

Figure 3. Feature points for unstructured roads.

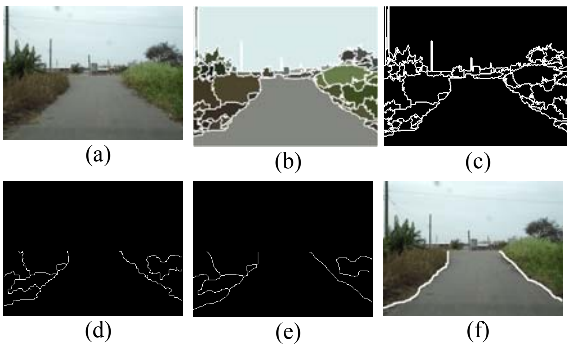

Figure 4. Lane detection process for unstructured roads.

Figure 5. Lane detection results.

Figure 4 displays an example of the intermediate result after each step in the unstructured lane detection process. Figure 4 (a) is the original image frame; Figure 4 (b) is the mean-shift segmentation result; Figure 4 (c) shows the region boundaries; Figure 4 (d) displays the boundaries that are below the vanishing line after region merging and skeletonization; Figure 4 (e) shows the collection of the smoothed candidate boundaries; finally, Figure 4 (f) shows the most probable road boundaries. Selected lane detection results for structured and unstructured roads are displayed in Figure 5. The proposed system reaches an overall accuracy rate of 97.39%. The lane detection accuracy is computed based on the number of frames in which the lane boundaries are successfully detected, which is counted manually.

5. CONCLUSIONS

In order to be able to achieve high accuracy in lane detection with both structured and unstructured roads, we design a hierarchical lane detection system. Rather than trying to deal with all situations with one complicated algorithm, we classify the environment first before applying appropriate algorithms for different types of roads. In this way we are able achieve high accuracy with simple and efficient lane detection algorithms. For environment classification, pixels with lane-marking colors are extracted as feature points. Since the feature vectors are of high dimension, EDRDA is utilized in model selection and maximum likelihood estimation of Gaussian parameters. For structured roads, we utilize lane-marking color information and perform angle of inclination and turning point searching after moving vehicle elimination procedure. For unstructured roads, mean-shift segmentation is applied to divide the scene into regions. Possible road boundary candidates are selected from the region boundaries. Afterwards, Bayes rule is used to choose the most probable boundary pairs from the candidate boundaries. The proposed system is able to robustly find the boundaries of the lane in various weather conditions and is not affected by the passing traffic. When the vehicle switches from one type of road to another, the environment classification result will indicate that a different algorithm should be used and therefore the accuracy will not be deteriorated.

6. ACKNOWLEDGEMENT

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7. REFERENCES

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