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A Hierarchical Approach for Road Detection

Keyu Lu, Jian Li, Xiangjing An and Hangen He

***Abstract*— Road detection is a crucial problem for autonomous navigation system (ANS) and advance driver-assistance system (ADAS). In this paper, we propose a hierarchical road detection method for robust road detection in challenging scenarios. Given an on-board road image, we first train a Gaussian mixture model (GMM) to obtain road probability density map (RPDM), and next oversegment the image into superpixels. Based on RPDM and superpixels, initial seeds are selected in an unsupervised way, and the seed superpixels iteratively try to occupy their neighbors according to GrowCut framework, the road segment is obtained after convergency. Finally, we refine the road segment with a conditional random field (CRF), which enforces the shape prior on the road segmentation task. Experiments on two challenging databases demonstrate that the proposed method exhibits high robustness compared with the state-of-the-art.**

I. INTRODUCTION

Research on autonomous navigation system (ANS) and advance driver assistance system (ADAS) have attracted keen attentions in past several decades. One important issue of these systems is vision-based road detection, which is a binary labeling problem trying to label every pixel in the given road image with the category (road or background) it belongs to. However, road detection is still a challenging job due to the diversity of road scene with different geometric characteristics (varying colors and textures) and imaging conditions (different illuminations, viewpoints and weather conditions).

The road detection problem has been intensively studied in recent years. Some methods are based on color and texture features, e.g. the method presented in [1] used HSI color spaces as features for road detection, while the algorithm proposed in [2] combines texture and color features. However, in many offroad environments, texture and color features of road and its surroundings are quite complex and diverse, and sometimes it is extremely difficult to distinguish road regions from its surroundings by only using texture and color features. Another approach for road detection is based on road boundaries, the proposed method in [3] used road boundaries to fit a road curvature model for road detection. However, this kind of approaches do not appropriately behave when there is no evident borders (e.g., unstructured roads). More recently, vanishing point is used for road detection in [4] and [5]. This kind of methods does not work well when there is no obvious road vanishing point or the road has curved boundaries [6]. To deal with curved boundaries, in paper [7], the authors proposed to use the illuminant invariance to detect road regions. This approach is robust to illuminations, shadows and curved road. However, it doesn't contain any road shape prior information and is sensitive to noise. To make sensible use of prior information, in [8], road priors obtained from geographic information systems (GISs) are combined with the road cues estimated from current image to achieve robust road segmentation. However, the method may fails when there is no GIS database. Without GIS or map, Sotelo *et al.* [9] uses road shape restrictions to enhance the road segmentation. To make better use of road shape prior, He *et al.* [6] proposed to use road shape prior in the road segmentation by encoding the prior into a graph-cut framework, but the method would be suboptimal when the features of road and background are similar.

In this paper, we introduce a hierarchical road detection model to address this problem. In more detail, the proposed road detection architecture is depicted in Fig. 1. The proposed model relies on four main components:

1) Gaussian Mixture Model (GMM): We first employ GMM [10] to produce a pixel-wise road probability density map (RPDM), which shows the probability of road pattern to be presented at each pixel. The GMM is trained online using Expectation-Maximization (EM) algorithm [11].

2) Unsupervised Seeds Selection at Superpixel Level: The image is first over-segmented into superpixels due to the fact that superpixels are more perceptually meaningful, representatively, near-complete and computationally efficient than pixel grids and rectangular patches [12, 13]. Then pixel-wise RPDM is transferred to the level of superpixel. Superpixel-wise RPDM is used to obtain seeds, which are key elements of GrowCut [14].

3) GrowCut Framework: The initial road segment is obtained using GrowCut [14], which is an interactive segmentation framework based on Cellular Automaton (CA) theory [15]. As seed points are automatically selected by superpixel-wise RPDM, GrowCut becomes an unsupervised process and does not rely on the interactive property. For road segmentation task, each superpixel is regarded as a cell with a label (road or background), the initial road segment is obtained when cell evolution stops. GrowCut is applied to overcome the shortcomings of [6].

4) Conditional Random Field: In order to get rid of the shortcomings of illuminant invariance based method [7] and ensure that the road segment is globally consistent, inspired by [6], we employ a conditional random field (CRF) to integrate road shape prior into the road segment. We combine the road segment with road shape prior by adding a second-order term to the basic CRF energy function.

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Keyu Lu, Jian Li, Xiangjing An and Hangen He are with the College of Mechatronics and Automation, National University of Defense Technology, Changsha 410073, China lkyer100@gmail.com

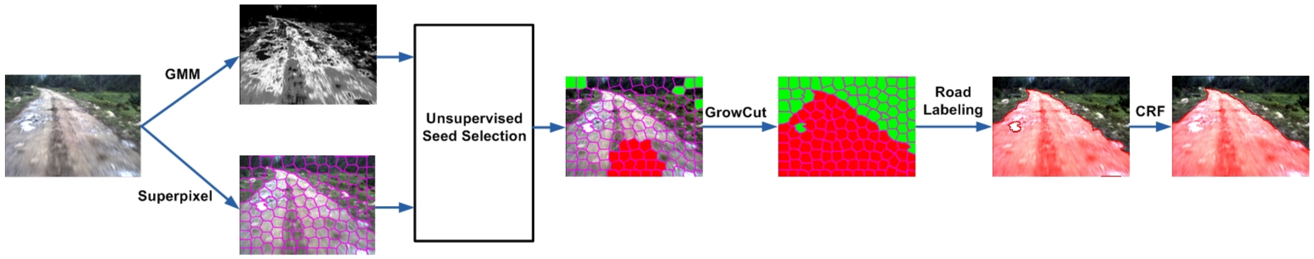
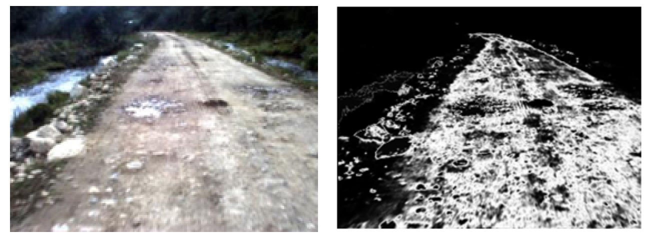


Fig. 1. Diagram of our hierarchical road detection model.

Fig. 2. Illustration of the sampling region.



(a) (b)

Fig. 3. Example of a RPDM computed by the probability density function: (a) The original road image. (b) The RPDM of the image, the brighter the pixel, the higher the probability density.

The rest of this paper is organized as follows. In Sec. II we introduce the proposed hierarchical road detection method. The performance of the proposed model is evaluated in Sec. III, while conclusions are drawn in Sec. IV.

II. Method

A. Online Learning of Gaussian Mixture Model

For road detection problem, there are two patterns in each road image: road pattern and background pattern. In order to estimate the probability density function of the road pattern online, we first define a Gaussian mixture model (GMM) [10] in RGB color space. Let K be the number of components of GMM and $x \subset R^3$ be a RGB value of a pixel. The probability density function of the road pattern $f(x)$ can be written as:

$$f(x) = \sum_{k=1}^{K} \rho_k g(x|\mu_k, \sigma_k^2), \tag{1}$$

where each $\rho_k > 0$ is a mixing weight and $g(.)$ is a Gaussian distribution:

$$g(x|\mu_k, \sigma_k^2) = \frac{1}{\sigma_k \sqrt{2\pi}} \cdot e^{\frac{-(x-\mu_k)^2}{2\sigma_k^2}}. \tag{2}$$

With the common assumption [16, 17], we define a "safe" window $C_{a,b}$ in the road image and assume that the pixels in the "safe" window belong to the road pattern. (see Fig. 2, the "safe" window is a semiellipse at the central-bottom of the on-board road image). We sample pixels from the "safe" window $C_{a,b}$ to train the Gaussian mixture model online.

We use Expectation-Maximization (EM) algorithm [11] to learn the parameters (μ_k, σ_k^2) from a given road image. Let X denote a set of samples following the Gaussian distribution $g(x|\mu_k, \sigma_k^2)$, maximum likelihood function is given in Eq. (3).

$$L(X|\theta) = \prod_{n=1}^{K} g(x|\mu_k, \sigma_k^2), \tag{3}$$

where θ denotes the set of parameters of GMM. The EM algorithm is an iterative approach and starts with θ_0:

$$\theta_0 = (\rho_1^{(0)}, \ldots, \rho_k^{(0)}, \mu_1^{(0)}, \ldots, \mu_k^{(0)}, \sigma_1^{2(0)}, \ldots, \sigma_k^{2(0)}), \tag{4}$$

where $\rho_1^{(0)}, \ldots, \rho_k^{(0)}$ are initialized by K-means algorithm [18].

The algorithm consists of two steps:

1) Expectation

As shown in Eq. (5), this step computes $Q(\theta, \theta_{t-1})$ using the set of parameters θ_{t-1} and training data X which is sampled from the region defined in Fig. 2.

$$Q(\theta, \theta_{t-1}) = E[L(X|\theta)|X, \theta_{t-1}]. \tag{5}$$

2) Maximization

This step computes the set of parameters θ_t by maximizing $Q(\theta, \theta_{t-1})$:

$$\theta_t = \arg\max_{\theta} Q(\theta, \theta_{t-1}). \tag{6}$$

We can get the set of the parameters θ_t for next iteration from Eq. (6). Step 1) and 2) are repeated until convergence.

When the parameters (μ_k, σ_k^2) of a Gaussian mixture model are obtained, we can compute the road probability density map (RPDM) of the given image using the probability density function (see Fig. 3).

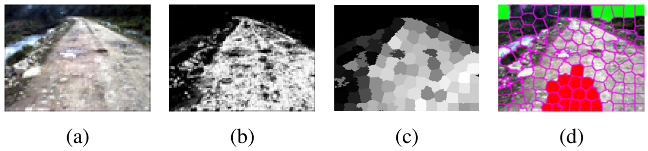


Fig. 4. Automatic selection of seed points at superpixel level: (a) The original road image. (b) The pixel-wise RPDM, the brighter the pixel, the higher the probability density. (c) The superpixel-wise RPDM, the brighter the superpixel, the higher the probability density. (d) Image with selected seed points, road seeds are colored in red, background seeds are colored in green.

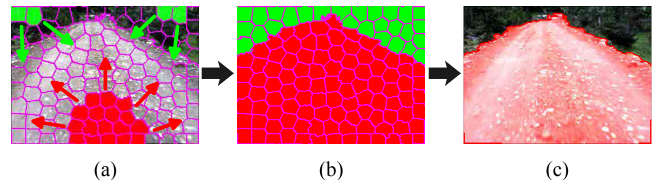


Fig. 5. Illustration of segmentation using GrowCut: (a) The seed superpixels iteratively try to occupy their neighbors according to Cellular Automaton, (b) All the superpixels will converge to stable configuration, (c) Road segment is obtained from the result of GrowCut.

B. Seeds Selection at Superpixel Level

In order to produce spatially more appealing road segments, inspired by [19], we firstly perform a preliminary over-segmentation of the given road image into superpixels using SLIC [20]. Rather than using the pixel grids and rectangular patches, superpixels tend to preserve boundaries and are most likely uniform in color and texture, so they are more perceptually meaningful and representationally efficient [12]. Furthermore, they dramatically reduce computational complexity of subsequent image processing tasks (such as GrowCut) [13].

Having obtained superpixels, we next compute the RPDM at superpixel level. Let D be the RPDM at superpixel level, the probability density D_k at superpixel k can be estimated using the RPDM at pixel level M (see Fig. 4):

$$D_k = \frac{\sum_{i \in S_k} M_i}{N_k}, \tag{7}$$

where S_k denotes the set of pixels that belong to superpixel k , N_k denotes the number of pixels in superpixel k.

Having obtained superpixel-wise RPDM, seeds can be automatically selected (see Fig. 4). Superpixels which are marked as road are called road seeds, while marked as background are called background seeds. As shown in Fig. 2, We assume that pixels in the region $C_{a,b}$ all belong to road region. If two thirds of pixels in a superpixel are in the region $C_{a,b}$, the superpixel is defined as road seed. Background seeds are selected using superpixel-wise RPDM. For a RPDM at superpixel level D, the threshold T_J is obtained using Eq. (8):

$$T_J = \min D + \frac{\max D - \min D}{U}, \tag{8}$$

where U is a constant which is assigned manually ($U = 100$ in our research). Superpixels with road probability density values less than T_J are set as background seeds.

C. Segmentation using GrowCut Framework

GrowCut [14] is a segmentation framework which follows Cellular Automaton (CA) theory [15]. GrowCut starts with a set of seed points, and the seed points iteratively try to occupy their neighbors according to Cellular Automaton until convergency. As seed points are automatically selected by superpixel-wise RPDM, GrowCut becomes an unsupervised process.

Having obtained seed points, the seed superpixels iteratively try to occupy their neighbors according to Cellular Automaton. For the superpixel p, let l_p denote the label (road or background), $\overrightarrow{I_p}$ denote the feature vector of the superpixel, and θ_p denote the strength, the state of the superpixel p can be defined by a triplet $(l_p, \overrightarrow{I_p}, \theta_p)$. Let R, G and B be three channels of a color road image, the feature vector $\overrightarrow{I_p}$ of the superpixel p is calculated using Eq. (9).

$$\overrightarrow{I_p} = \left(\frac{\sum_{i \in S_p} R_i}{N_p}, \frac{\sum_{i \in S_p} G_i}{N_p}, \frac{\sum_{i \in S_p} B_i}{N_p}\right), \tag{9}$$

where S_p denotes the set of pixels that belong to superpixel p , N_p denotes the number of pixels in superpixel p.

The strength θ_p is used to define the state transition rule for updating the states of superpixels at each iteration step and $\theta_p \in [0,1]$. Initially the strength is set to 1 for each seed superpixel and 0 for all other superpixels.

Let p be the attacking and q the attacked superpixel, then p occupies q if:

$$g(\left\|\overrightarrow{I_p} - \overrightarrow{I_q}\right\|_2) \cdot \theta_p > \theta_q, \tag{10}$$

where $g(x)$ is a monotonically decreasing function:

$$g(x) = 1 - \frac{x}{\max \left\|\overrightarrow{I}\right\|_2}. \tag{11}$$

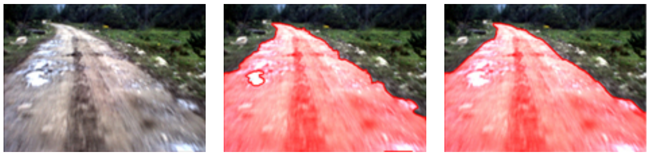
If p occupies q, then the label and strength of q will change according to the state of p:

$$\begin{cases} l_q = l_p \\ \theta_q = g(\left\|\overrightarrow{I_p} - \overrightarrow{I_q}\right\|_2) \cdot \theta_p. \end{cases} \tag{12}$$

Each superpixel in given road image tries to occupy its neighbors iteratively until all the superpixels converge to stable configuration. As shown in Fig. 5, the road segment is obtained after convergency.

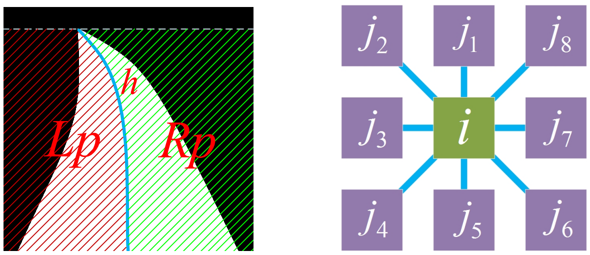
D. Refinement with a Conditional Random Field

In order to involve road shape prior, we implement a conditional random field (CRF) model at pixel level. The system with above steps already has the capability to detect the road region from a road image, but might still be prone to errors. We use a CRF model to integrate road shape prior and achieve a more robust detection (see Fig. 6).



(a) (b) (c)

Fig. 6. Refinement with a CRF: (a) The original road image, (b) The result of GrowCut, (c) The result of CRF.



(a) (b)

Fig. 7. (a) A road segment with the middle line h, Lp denotes the left part of h, Rp denotes the right part of h, (b) A standard 8-neighborhood system with a center pixel i and its neighbors $j_1 \dots j_8$.

To build the CRF model at pixel level, let l_i denote the label (road or background) of the pixel i and l denote the set of all label assignments. The CRF energy to minimize can be written as:

$$E(l) = \sum_{i \in V} \phi_i(\hat{l}_i, l_i) + \lambda \sum_{e_{ij} \in E} \psi_{ij}(l_i, l_j) + \sum_{e_{ij} \in E} \varphi_{ij}(l_i, l_j), \quad (13)$$

where ϕ_i is the unary term enforcing the label l_i (road or background) to take value close to the label $\hat{l}_i$ which is obtained from GrowCut stage, ψ_{ij} is the pairwise term penalizing the different assignments for neighboring pixels i and j, and φ_{ij} is the second-order term involving road shape prior. The unary term takes the form:

$$\phi_i(\hat{l}_i, l_i) = \begin{cases} 1 & \hat{l}_i \neq l_i \\ 0 & \hat{l}_i = l_i \end{cases}, \quad (14)$$

where $\hat{l}_i$ corresponds to the label of pixel i obtained from GrowCut stage. Let $\overrightarrow{C_i}$ be three-dimensional color vector of pixel i in RGB color space, the pairwise term follows the form:

$$\psi_{ij}(l_i, l_j) = \begin{cases} \exp(-\beta \left\| \overrightarrow{C_i} - \overrightarrow{C_j} \right\|_2) & l_i \neq l_j \\ 0 & l_i = l_j \end{cases}. \quad (15)$$

Inspired by [6], we propose a second-order term φ_{ij} to incorporate road shape prior into the CRF framework. The road shape prior is based on geometric properties of the road in an on-board road image.

We assume that the road segment in Fig. 7(a) is the result of GrowCut stage, the middle line h can be obtained easily, let Lp be the left part of h and Rp the right part of h. i is an arbitrary pixel in the road segment, $j_1 \dots j_8$ are neighbors of i (see Fig. 7(b)). The road shape implies that:

TABLE I

PERFORMANCE METRIC.

Pixel-wise measure	Definition
Recall	$R = \frac{TP}{TP+FN}$
Precision	$P = \frac{TP}{TP+FP}$
F-measure	$F = \frac{2PR}{P+R}$
Quality	$\hat{g} = \frac{TP}{TP+FP+FN}$

$$\begin{cases} \forall i, (i \in Lp) \wedge (j_3 \in Road) \Rightarrow i \in Road \\ \forall i, (j_7 \in Lp) \wedge (i \in Road) \Rightarrow j_7 \in Road \\ \forall i, (i \in Rp) \wedge (j_7 \in Road) \Rightarrow i \in Road \\ \forall i, (j_3 \in Rp) \wedge (i \in Road) \Rightarrow j_3 \in Road \end{cases}. \quad (16)$$

Eq. (16) is incorporated into CRF energy function by second-order term φ_{ij}:

$$\varphi_{ij}(l_i, l_j) =$$

$$\begin{cases} \infty & if\,\{(l_i = 0 \; and \; l_j = 1 \; and \; i \in Lp \; and \; j = j_3) \\ & or\; (l_i = 1 \; and \; l_j = 0 \; and \; j \in Lp \; and \; j = j_7) \\ & or\; (l_i = 0 \; and \; l_j = 1 \; and \; i \in Rp \; and \; j = j_7) \\ & or\; (l_i = 1 \; and \; l_j = 0 \; and \; j \in Rp \; and \; j = j_3)\} \\ 0 & \text{otherwise} \end{cases}, \quad (17)$$

where 1 stands for road segments and 0 stands for background. The CRF energy $E(l)$ in Eq. (13) is minimized using graph cut [21].

III. Result and Discussion

We evaluate the performance of the proposed approach on two challenging databases, one is a subset of SUN database [22], and the other is OffRoadScene database [23]. For brevity, the method using Gaussian mixture model defined in part III is abbreviated to "GMM", the method based on GrowCut at pixel level is denoted by "p-GrowCut", the method using GrowCut at superpixel level is denoted by "s-GrowCut" and the one based on CRF is denoted by "CRF". We compare next our method (GMM + s-GrowCut + CRF) with different combination of "GMM", "p-GrowCut", "s-GrowCut" and "CRF". For further analysis, we also compare our proposed method with two state-of-the-art road detection algorithm: Kong *et al*. method [4] and Álvarez *et al*. method [7].

As shown in TABLE I, quantitative evaluations are provided using 4 types of pixel-wise measures: recall (R), precision (P), F-measure (F) and quality ($\hat{g}$). In TABLE I, TP and TN denote the number of road pixels correctly detected and background pixels correctly detected, respectively. FP and FN denote the number of background pixels incorrectly marked and road pixels incorrectly identified, respectively.

A. Experiment on SUN database

SUN database [22] is a well-known database for scene recognition. The database contains 899 categories and a total of 130519 images. For road detection task, we randomly

TABLE II
QUANTITATIVE RESULTS ON SUN DATABASE [22].

Method	R(%)	P(%)	F(%)	$\hat{g}$(%)
GMM	65.2	56.3	62.1	46.6
GMM + CRF	72.7	72.9	70.2	56.4
GMM + p-GrowCut	76.3	74.5	70.8	69.3
GMM + s-GrowCut	88.3	82.8	85.2	73.1
Kong *et al.* method [4]	77.2	75.1	76.6	63.2
Álvarez *et al.* method [7]	88.5	83.8	82.5	72.3
Our proposed method	**91.1**	**86.7**	**88.2**	**79.5**

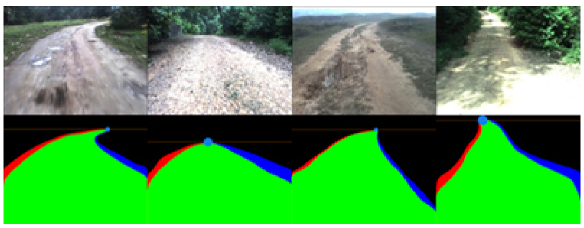


Fig. 8. Images with ground truths in the database. The first rows are original images, The second rows are the corresponding ground truths, road region is marked with green color, ambiguous regions of left and right edge are marked with red and blue colors, respectively.

select 400 on-board road images to compose a test set. The ground truth of the test set is manually labeled. As shown in TABLE II, the performance of our approach on this database appreciably outperforms the other six methods.

B. Experiment on OffRoadScene database

We also measure our performance on OffRoadScene database [23], which consist of 770 unstructured road images which are captured by driving on several unstructured roads. The database contains various types of road scene with different texture, shadows, illuminations, and weather conditions. All the images are resized to 320×240 for testing. The ground truth of the database is manually labeled. As most of the unstructured roads have no clear borders, the database uses ambiguous regions to describe the road borders, as shown in Fig. 8, the ambiguous regions are unconcerned to experimental results. Quantitative results is shown in TABLE III.

C. Discussion

Some qualitative results of two databases can be seen in Fig. 9. As shown in TABLE II, TABLE III and Fig. 9,

TABLE III
QUANTITATIVE RESULTS ON OFFROADSCENE DATABASE [23].

Method	R(%)	P(%)	F(%)	$\hat{g}$(%)
GMM	64.3	55.5	59.8	43.7
GMM + CRF	70.2	69.6	68.5	54.7
GMM + p-GrowCut	74.2	72.7	69.8	59.1
GMM + s-GrowCut	87.5	81.1	82.8	72.3
Kong *et al.* method [4]	75.1	74.3	74.7	63.5
Álvarez *et al.* method [7]	84.3	77.9	79.8	69.6
Our proposed method	**89.9**	**85.5**	**87.6**	**78.1**

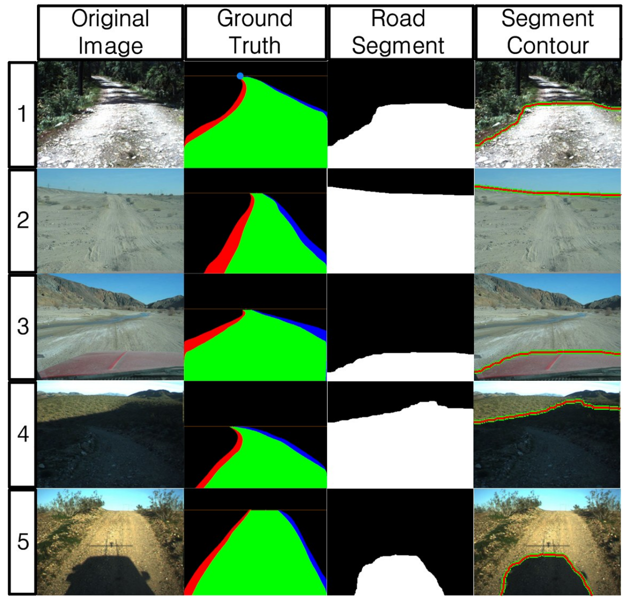


Fig. 10. Hard image cases of our proposed method.

our proposed method performs much better than other six methods. These results also indicates that:

1) The performance is improved significantly (more than 15%) when Gaussian mixture model and superpixel-based GrowCut are combined, but combining Gaussian mixture model and pixel-based GrowCut exhibits little performance. This is due to rapid decline in cell strength when GrowCut runs in pixel level.

2) Our hierarchical model (GMM + s-GrowCut + CRF) benefits from CRF which enforces the road shape prior on the road segmentation task and makes the road segments more look like road (see Fig. 9, row 5).

3) Kong *et al.* method [4] does not work well when the road boundaries are curved (see Fig. 9, row 2, 4), and Álvarez *et al.* method may fails when some parts of road and background are similar (see Fig. 9, row 1, 3). Yet, our proposed method exhibits high robustness against road scene variations.

Although our proposed method has performed well in the experiments, it does fail in certain cases. As shown in Fig. 10, the proposed method could not satisfactorily detect road from several "hard" images. We conclude that our method may fail in following cases:

1) Heavy shadow appear on certain parts of road (row 1, 4, 5);

2) Color features of road and background are too similar (row 2);

3) Some parts of the sampling region are covered by objects (row 3).

One way to get rid of these shortcomings is to explore global sampling strategies and employ more complex features (e.g., a better feature that is robust to shadow), which are our interesting directions for future work.

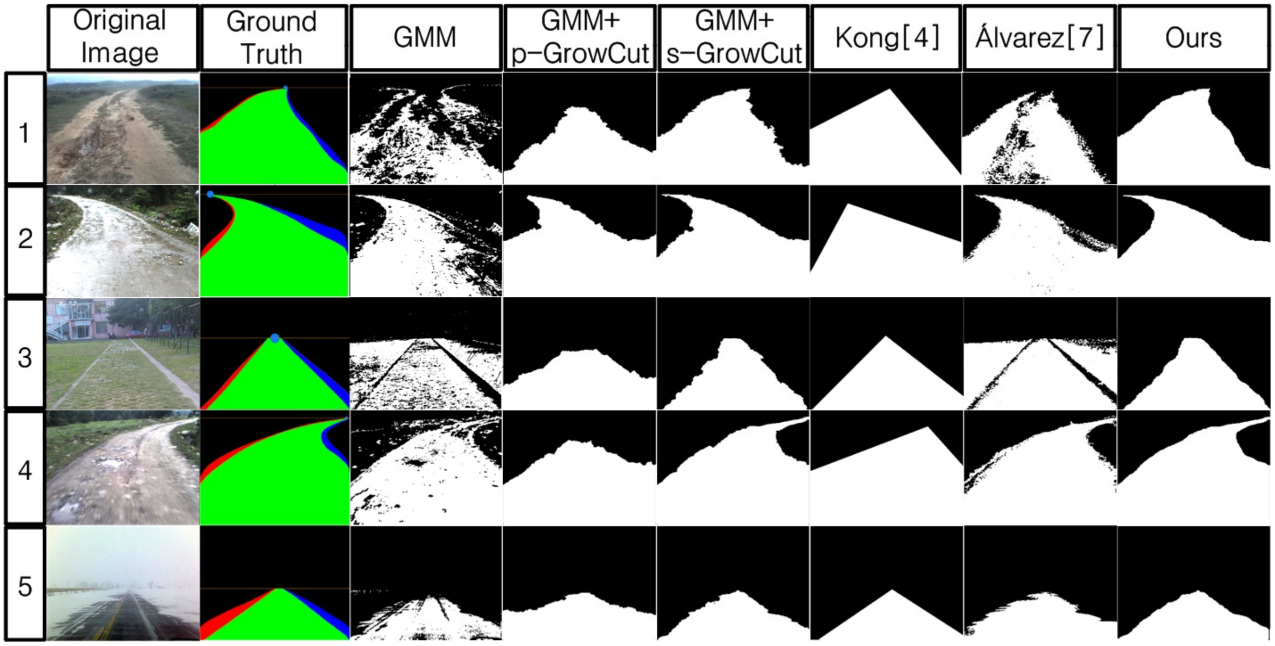


Fig. 9. Qualitative Comparisons of different method. Road and background regions in column 3∼8 are marked with white and black, respectively.

IV. CONCLUSIONS

In this paper, we propose a hierarchical road detection model which consists of four major components: Gaussian mixture model, GrowCut based segmentation, superpixel-wise seeds selection and conditional random field. Experimental results on two challenging databases demonstrate that the proposed approach is able to exhibit high robustness compared with some state-of-the-art approaches. To achieve better performance, our future work includes exploring global sampling strategies and employing better features which will be robust to shadow.

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