International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 6 Issue 1 ǁ 1. 2018 ǁ PP. 13-20

Research On Road Detection Based On Improved RANSAC Algorithm

[1]Ming Xu, [2]Juan Zhang, [3]Zhijun Fang*
Shanghai University of Engineering Science, School of Electrical and Electronic Engineering, Long Teng Road, Shanghai, China, 201620
Corresponding Author: 2 Juan Zhang

ABSTRACT: Road detection is one of the most important contents of automatic driving technology in recent years. In this paper, an improved RANSAC algorithm is proposed to detect boundaries of roads in unstructured environments, which is adapted to various unstructured scenes, such as uneven illumination and water stained pavements. The procedure of road detection includes 4 main parts: firstly, reducing the computational complexity by acquiring regions of interest. Secondly, 2-dimensional Otsu algorithm is used to segment the road from the background. Subsequently the whole road area is obtained by mathematical morphological operation and the method of getting the largest connected area. Edge detection and road boundaries extraction are used to get the information of road boundaries. Finally, an improved RANSAC algorithm is applied under the cubic curve model to fit the points of road boundaries. The experimental results show that the method can not only detect straight roads, but also apply to winding roads, and has good robustness and anti-interference to the road affected by shadows and water stains.

Keyword: Road detection, road boundaries extraction, image segmentation, RANSAC algorithm

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Date of Submission:12-12-2017 Date of acceptance: 12-01-2018

I. INTRODUCTION

In recent years, with the popularity of private cars, road traffic accidents are becoming increasingly frequent. As a new technology in the new field, auxiliary driving technology has attracted much attention due to its extensive prospects. Vision-based road detection technology is one of the important elements of the advanced assistant driving system (ADAS), which is usually applied to the extraction of lane markings1-3. Since most lanes on the highway have clear lines and most of them are straight lines so that it is easy to detect the lanes and the lane detection technology for structured roads has reached a high level during recent years. However, due to inhomogeneous surface and curved shape of the roads, and the unstructured roads are vulnerable to light, shadow, water and other factors, which leads to poor detection performance. Therefore, the unstructured road detection technology is still in the research period.Taking the characteristics of various road models and the actual needs of road detection into consideration, we propose a fast and efficient road detection algorithm that can detect the unstructured road affected by complex environments. The procedure of the proposed method is as follows. Firstly, region of interest (ROI) is obtained to preclude interference of the environments. Then 2-dimentional Otsu algorithm is used to segment the ROI image. After a series of procedures, such as mathematical morphological operation and the largest connected area extraction, a complete road area is acquired, edge detection and road boundaries extraction are also used to get the information of boundaries of the road. Ultimately, an improved RANSAC algorithm is adopted under the cubic model to fit the points of road boundaries.The rest of the paper is organized as follows. Sec. 2 introduces related works on road lane detection in recent years. Sec. 3 describes the proposed detection method on unstructured road. Sec. 4 shows experimental results under different scenes. The conclusion and further research suggestion demonstrate in Sec. 5.

II. RELATED WORKS

For an autonomous driving system, it is critical to detect and track the lane markings or road boundaries under various environmental conditions, which is also significant for the navigation and departure warning[4,5]. In this section, we illustrate some documents related to the research of road detection in recent years. At present, domestic and foreign research scholars have presented plenty of methods used to detect the road[6,7]. These algorithms can be roughly divided into three types: feature-based algorithm[8-11], model-based algorithm[12-14] and neural network based algorithm[15-18].

Feature-based algorithm deals with images according to features such as color, texture and edge. Methods based on features usually depend on road with relatively clear boundaries. In addition, pictures captured are vulnerable to the influence of shadows and uneven-illumination, which may bring about false detection of the road area. Ying Z, Li G and Tan G[8] proposed an illumination-robust approach for feature-based road detection. They modified saturation during preprocessing so as to diminish cast shadows, after acquiring ROI, an improved feature-based method is employed to identify lane-markings from the shadows.

Model-based method greatly depends on the setting of model parameters to acquire the boundaries of the road. Due to the reality of the road model is a linear or curved shape, it is easy to fit the road boundaries with Hough transform and Least Square Method. However, both of the methods have difficult in adjusting to the continuous changing environment. Shikun Xu et al.[12] obtain a "bird's eye view" of the road by using IPM transform. Subsequently, an improved RANSAC algorithm is implemented to fit hyperbolic model, which ensures the high robustness and efficiency of the algorithm.

Neural network based approach is an increasingly popular method during these 5 years. This method deals with data collected and learn features that commonly exist in images of the data set. After finishing the procedure of training, the system can easily recognize and classify what they are once you input wanted data. However, this method has its shortcomings that a quite large data set is needed and a long-term training process is required. Junyu Gao et al.[16] proposed a siamesed fully convolutional network based on VGG-net architecture, which is able to consider RGB-channel, semantic contour and location prior simultaneously to segment road region elaborately.

Recent years, many researchers have been considering combine features with neural network to solve problems. Wenli He et al.[19] developed a robust feature fusion framework, which is combined with superpixel feature and 3D feature extracted from stereo images. Then a neural network classifier is applied to judge if a superpixel is a road region or not. Furthermore, there are some documents integrating method based on features into model-based algorithm. Liying Wu and Qiang Yu[20] present an approach based on gray feature and road model to process the road images. 2-D maximum entropy is used to segment the road and fuzzy entropy is utilized to optimize segmentation results according to the gray feature of the images. And an improved method of fitting is put forward on the basis of least squares curve fitting.

III. PROPOSED METHODS

The proposed method includes four main parts: ROI selection, road image segmentation, road boundaries extraction and road boundaries modeling and fitting. Firstly, selecting a ROI in order to reduce the computational complexity as well as exclude part of interference. Secondly, segmentation algorithm based on 2-D Otsu is used to obtain a binary road image separated from the non-road area. Thirdly, mathematical morphological open and close operation to fill the holes in the image, and the largest connected area is extracted from the image, which is considered as the entire road area. Besides, road boundaries are acquired by edge detection operator and the method of road boundaries extraction. Finally, an improved RANSAC algorithm under the cubic curve model is applied to fit the points of boundaries.

3.1 Region of Interest Selection

As we know, the camera is usually placed on the top of a car, the road images it takes usually contain some irrelevant information such as the sky. So some articles[21,22] mentioned that they set a ROI manually which is often located in the bottom of the image so as to reduce some interference. However, the road pictures taken by camera during driving vary widely. If we use the bottom of the images casually, it is likely to cause problems for following procedures such as road detection and boundaries fitting. Therefore, this method cannot effectively determine the ROI of the road. In order to detect the road more precisely and reliably, we adopt the algorithm of Ref. 23 to detect the vanishing point. The main proposed method is to implement edge detection, then Hough transform is used to find the intersection point of the road, which is seen as the vanishing point. The horizontal line of vanishing point is called the vanishing line, so that picture under the vanishing line is thought as the ROI. Meanwhile, the algorithm may lead to wrong results. Hence we choose the bottom 2/3 area of the image if the algorithm detects a wrong vanishing point located in the top 1/3 area.

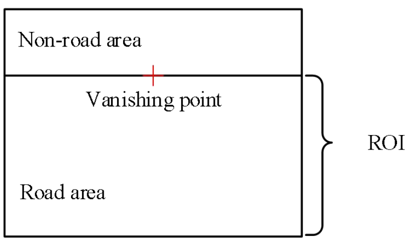


Fig. 1 Layout of the road area

Fig. 2 Road image with vanishing point

Fig. 3 ROI image

3.2 Road Segmentation Based on 2-Dimentional Otsu Algorithm

Otsu is a typical dynamic threshold method. The method takes the maximum variance of the target and the background as the criterion in choosing a threshold, and takes the gray value when the maximum variance is generated as the overall segmentation threshold of the image so as to achieve the purpose of region segmentation. Compared to Otsu, 2-D Otsu considers both gray information of the image and spatial neighborhood information between pixels, which also has the advantage of higher noise immunity[24]. The concrete steps are as follows:

1) Get the 2-dimentional histogram h_{ij} according to an image (size: $M \times N$) whose gray level is L and neighborhood smoothing image g , h_{ij} stands for the image whose original image with a gray level of i and a smoothing image with a gray level of j . So the joint probability of i and j is $P_{ij} = h_{ij} / (M \times N)$.

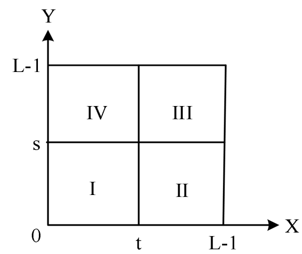


Fig. 4 2-D grayscale histogram

2) For the 2-dimentional histogram shown in Fig. 4, t represents gray levels of the image, s stands for gray mean value of pixel neighborhood. Because of the self-similarity of the feature of object and background, which will be located in the area I and area III (presume that they are background and object respectively) so that we will obtain the possibility of background ω_0 and object ω_1 .

$$\omega_0 = \sum_{i=0}^{s}\sum_{j=0}^{t} P_{ij} , \omega_1 = \sum_{i=s+1}^{L-1}\sum_{j=t+1}^{L-1} P_{ij}$$

And the mean value of gray image of the background and object are:

$$\overline{u}_0 = (u_{0s,} u_{0t})^T = (\sum_{i=0}^{s}\sum_{j=0}^{t} iP_{ij} / \omega_0 , \sum_{i=0}^{s}\sum_{j=0}^{t} jP_{ij} / \omega_0)^T$$

$$\overline{u}_1 = (u_{1s,} u_{1t})^T = (\sum_{i=s+1}^{L-1}\sum_{j=t+1}^{L-1} iP_{ij} / \omega_1 , \sum_{i=s+1}^{L-1}\sum_{j=t+1}^{L-1} jP_{ij} / \omega_1)^T$$

The mean value of the whole gray image is:

$$\overline{u}_T = (u_{Ti,} u_{Tj})^T = (\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} iP_{ij} , \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} jP_{ij})^T$$

3) Set (s,t) as the threshold of segmentation that meets the demand of the largest variance between classes.

$$\arg\max_{s,t} S_B(s,t) = \omega_0(\overline{u}_0 - \overline{u}_T)^2 + \omega_1(\overline{u}_1 - \overline{u}_T)^2$$

S_B is the matrix which is used to denotes the degree of segmentation between object and background.

The final segmentation threshold is taken as the parameter of adaptive threshold segmentation, and the gray image of ROI is segmented to obtain a binary image which separates the road area from the non-road area.

3.3 Road Boundaries Extraction

This section focuses on further optimization of the road image after segmentation, to make the edge of the road clearer and more conducive to road fitting. The main steps of road boundaries extraction in this paper are as follows:

1. Mathematical morphology operation: Due to the large amount of irrelevant noise in the vicinity of unstructured road, which may influence the acquisition of road area. Therefore, this paper uses morphological open and close operations to eliminate holes as well as smooth the road boundaries.
2. Road area acquisition: In this paper, the method of obtaining the largest connected domain is adopted. After marking each connected domain, the area of each region is calculated and the area with the largest proportion is selected as the road area.
3. Edge detection: This paper uses Sobel operator for edge detection. Sobel operator has a smoothing effect on the noise, which provides more accurate edge direction information. The information of road boundaries is gotten after the edge detection.
4. Road Boundaries Extraction: Since two sides of the boundaries cannot be fitted on one map at the

same time, the left and right boundaries should be separated and fitted in turn. The image after the edge detection is a binary image $E(x,y)$ containing only two types of pixels (0/1).

$$E(x,y)=\begin{cases}1, \textit{points of boundaries}\\0, \textit{else}\end{cases}$$

The method of scanning seeks points that pixel are 1 in the image from the top to the bottom sequentially. If there are no less than 2 points whose pixel are 1 in a row, put the first point into an image ω_1, and store the last point into another image ω_2 (Both ω_1 and ω_2 are images have the same size as ROI and store zeros only). At last, we will obtain an image ω_1 with points of the left boundary only, and another image ω_2 with points of the right boundary only.

$$\textit{road boundaries}:\begin{cases}\omega_1, \textit{the left boundary}\\\omega_2, \textit{the right boundary}\end{cases}$$

3.4 Road Boundaries Modeling and Fitting

3.4.1 Road boundaries modeling

The commonly used road fitting model are linear model[25], quadratic curve model[26] and cubic curve model[27] and so on. The method based on the linear model is simple and has good real-time performance, but the disadvantage is that curved road cannot be fitted. The quadratic curve model extends the linear model and solves the problem that linear model cannot fit the curve road without increasing the complexity of the algorithm. However, like the linear model, the model has the problem of lower fitting accuracy due to disturbances of local interference points. The cubic curve model is suitable for the road whose curvature changes rapidly, but the model needs more calculations and produces poor real-time performance. By summarizing the advantages and disadvantages of these models, this paper chooses the cubic curve model M as the shape of unstructured road changes fast, and the model formula shows in ①:

$$y=ax^3+bx^2+cx+d \qquad ①$$

3.4.2 Road boundaries fitting

Hough transform used to fit the line on structured roads as the lanes on the structured roads are clear and usually linear lines. Fitting the road boundaries by Least Squares Method has the advantages of convenient calculation and good fitting effect. However, the method is more sensitive to outliers. When there are some outliers, it will lead to the deviation of the curve model. The RANSAC algorithm becomes widely used because it only fits the key points that are suitable for the pre-set model and is insensitive to outliers. Nevertheless, its disadvantages are also obvious, that is, we are supposed to set the number of iterations and a threshold related to the problem manually, which is hard to choose. In order to solve the problems above, this paper presents a method based on an improved RANSAC (RANdom SAmple Consensus) algorithm to fit the road boundaries. For fitting the left boundary, for example, the specific steps are as follows:

(1). Acquire the whole sample points. Take one point for every 2 lines, the point set obtained is the whole sample points.

(2). Divide all the sample points into 4 equal parts from top to bottom, and randomly select a sample point from each sample subset as the feature point. Assume the coordinate of the 4 feature points are $(x_1,y_1),(x_2,y_2),(x_3,y_3),(x_4,y_4)$, if they are on the curve, $[a,b,c,d]$ can be solved by following equations ②, which is the coefficients of cubic curve model.

$$\begin{cases}ax_1^3+bx_1^2+cx_1+d=y_1\\ax_2^3+bx_2^2+cx_2+d=y_2\\ax_3^3+bx_3^2+cx_3+d=y_3\\ax_4^3+bx_4^2+cx_4+d=y_4\end{cases} \qquad ②$$

(3). Calculate the shortest distance from the entire sample point to the curve model, which is accomplished by the Least Square Method. If a sample point satisfies the inequality ③, it is treated as the interior point of the curve. Continue to calculate the distance from remaining sample points to the curve model that is less than the threshold of the number of tolerances, counting the total number $t'(t'\le t)$ of all the inliers under this curve model.

$$min\,|ax_i^3+bx_i^2+cx_i+d-y_i|<\delta \qquad ③$$

(4). Set the number of iterations k and repeat steps ② and ③ above until the loop ends, and we will obtain k curve models.

(5). Specify the curve model with the largest number t' of inliers as the optimal curve model M^*, if the coefficients of the optimal curve model is $[a^*, b^*, c^*, d^*]$, the model formula shown in ④ is the final curve equation of the road boundary line:

$$y = a^*x^3 + b^*x^2 + c^*x + d^* \quad ④$$

Fig. 5 Fitting the left boundary

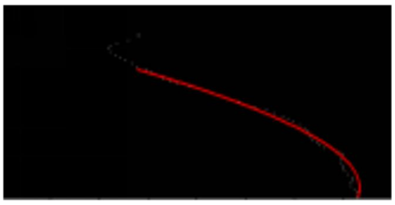


Fig. 6 Fitting the right boundary

Fig. 7 Image with fitting lines

The Fig. 5 and Fig. 6 above show fitting boundaries according to their points, and Fig. 7 displays the result on the original image. Compared to basic RANSAC algorithm, the improved RANSAC algorithm proposed in this paper is based on the understanding of prior knowledge of the road environment and selects various parameters suitable for unstructured environments. The concrete improvements are as follows:

1. Picking points at the same interval without affecting the whole boundaries points.
2. In order to reduce the randomness of the RANSAC algorithm, dividing the sample points into 4 equal parts, a random point is selected from each part.
3. The threshold δ is set to prevent inliers from being affected. Usually the threshold is hard to determine, but the points of road boundaries are often close to each other, so it is easy to set a fixed threshold and $\delta=10$ in this paper.
4. Number of iterations k is another value that needs to be improved. Some articles[12,28] directly set the number as 100 for the reason that multiple iterations are needed to ensure its accuracy. As we assume that the more points we have, the more iterations we need relatively, and vice versa. However, for some boundaries that have few outliers, finding the optimal curve model needs only several times iterations. So we set the number of iterations equals to a half of total number of sample points in order to select the iterations automatically and dynamically. Due to the procedure of ROI selection, the total number of sample points are generally no more than 100.

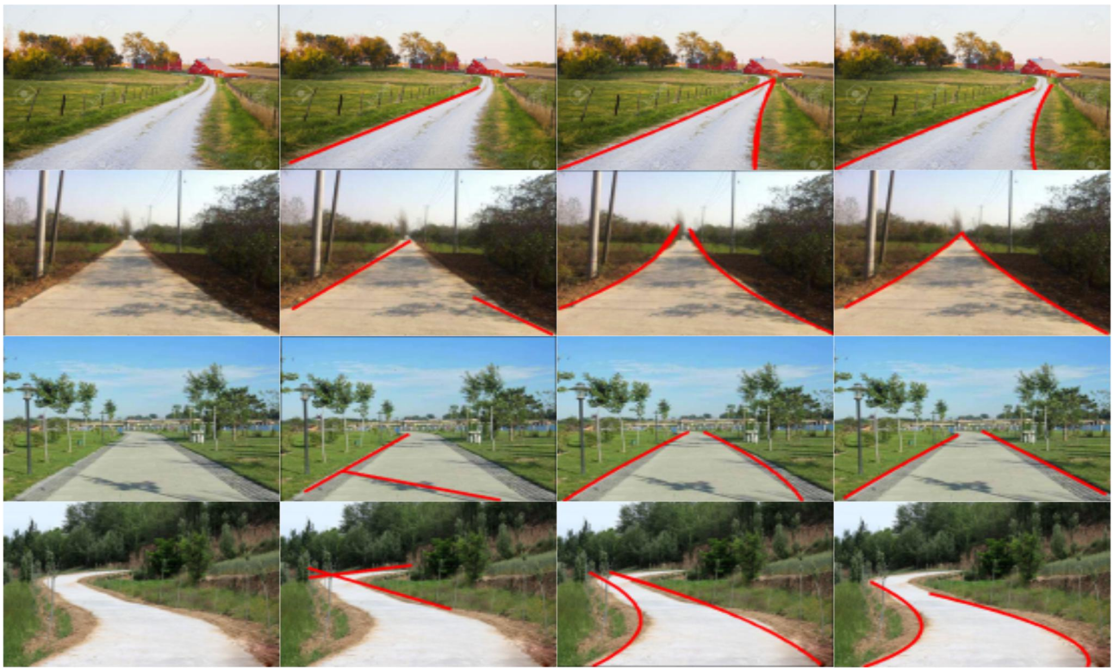
With the enhanced steps above, the improved RANSAC algorithm costs less consumption of time under the premise of fitting road boundaries.

VI. EXPERIMENTAL RESULTS

In order to verify the validity of the proposed algorithm, the author has conducted extensive tests on pictures with unstructured roads. Experiments were conducted in Windows 7 Ultimate system, and the MATLAB R2014a is used as a development tool. The size of test images are 400×300. In this paper, two groups of experiments are complemented to support the validation of our proposed method.

4.1 Experimental Results of Various Algorithms

In this section, Hough transform, Least Square Method and our method, containing linear model, quadratic curve model and cubic curve model respectively, are used on unstructured roads. As shown in Figure 8, there are several detection results of unstructured roads, of which (a) are original images, and (b), (c), (d) are detection results processed by Hough transform, Least Square Method and our method separately. As can be seen from Figure 8(b), Hough transform has high mistake rate and miss rate. As displayed in Figure 8(c), Least Square Method can obtain good detection results in some cases, but the false detection occurs in the shadow state and leads to fitting error on the road with large curvature. Compared with the former two algorithms, Figure 8(d) shows the proposed algorithm have better results in detecting the boundaries of various unstructured roads.



(a) (b) (c) (d)

Fig. 8 experimental results of various algorithms

4.2 Fitting Results under Different Environments of Unstructured Road

The following Fig. 9 shows the detection results processed by our method in different scenarios, such as light, shadow, mud, night, water and obstacles. Among these pictures, original images are shown in the 1st row; the gray images of ROI are presented in the 2nd row; binary images processed by 2-dimentional Otsu are in the 3th row; images after edge detection displayed in the 4th row; the 5th row shows detection results after improved RANSAC algorithm.

Fig. 9(a) shows the results of an image with low-illumination after processed by our method for each step. After the procedure of segmentation and edge detection, the image with complete boundaries is gotten. The result in the 5th row shows great fitting effects by improved RANSAC algorithm. Fig. 9(b) are images with the defect that original image has indistinct boundaries and its results after each detection results. As depicted in the 3rd row, the binary image after segmentation has a great deal of noises, which may have a bad influence on fitting the road boundaries. But the edge detection revised the road edges, and therefore an image with great fitting lines is acquired. Fig. 9(c) describes an image with water stained and its results after detection of each step. As we can see clearly that the image in the 4th row has a higher rate of false detection of the road boundaries. However, the 5th row indicates that the fitting procedure rules out false points of road boundaries and achieves favorable result. Fig. 9(d) reveals a road image with obstacles on the road and its detection results for every step. As the obstacle has similar gray levels, the segmentation step cannot tell obstacle and background apart. Edge detection removes some interference and fitting procedure ultimately contributes road boundaries roughly. Fig. 9(e) shows experimental results of the image with extensive shadow. Moreover, the image in the 5th row of Fig. 9(e) demonstrates our proposed method comes out favorable results even if in intense shadow. Fig. 9(f) displays an image under strong illumination and its detection results approached by our method. As we segment the image into a binary image, the entire road area is obtained so that it is easy to extract the points of road boundaries, and therefore successfully fits the road boundaries.

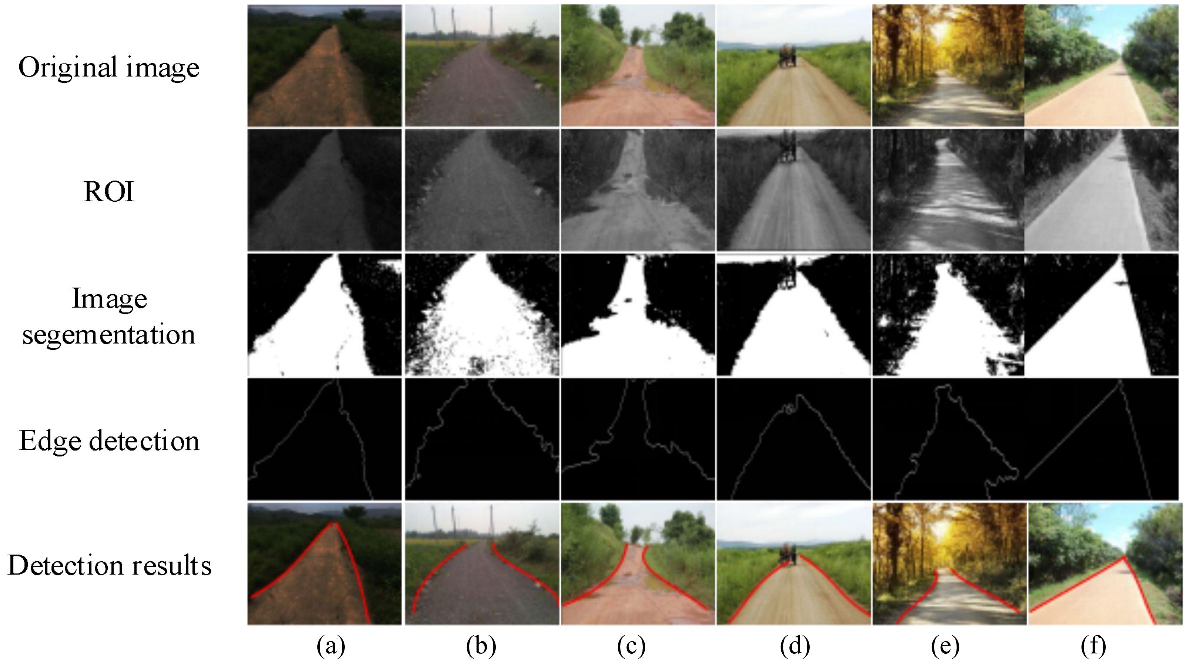


Fig. 9 Fitting results under different environments of unstructured road

VII. CONCLUSION AND FUTURE WORK

In this paper, we present an improved RANSASC algorithm to solve the problems of road detection on unstructured road. The proposed method needs preprossing procedures, such as ROI selection and 2-D Otsu algorithm to segment the road from the non-road areas. Mathematical morphological operation, the method of attaining the largest connected domain, edge detection and road boundaries extraction are used to extract the points of road boundaries. We propose an improved RANSAC algorithm under cubic curve model to fit points of road boundaries. The method gains promising results in various environments. In the future, we will be dedicated to deducing more effective and efficient methods to further improve the detection results and try to track road boundaries in the real world on a video.

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Ming Xu, "Research on Road Detection Based on Improved RANSAC Algorithm." International Journal of Research in Engineering and Science (IJRES), vol. 06, no. 1, 2018, pp. 13–20.