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A lane detection method based on target tracking approach

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ABSTRACT

Lane detection is important for the lane departure warning (LDW) for advanced driver assistance systems (ADAS). Several approaches for lane detection were suggested in the past. However, robustness is still an issue, in case the markings are not arranged in a straight line or when they are occluded. This paper presents a robust vision-based lane detection method. The key idea is to apply methods from the target tracking domain to identify lanes in the image space; we use an Interacting Multiple Model (IMM) approach to increase robustness. Our method is based on two phases: a preprocessing phase to extract areas that potentially represent markings and a tracking phase to identify the lanes. In the preprocessing phase, we use regions of interest, median filtering, Otsu's algorithm, and image erosion. The tracking is performed in spatial dimension and based on the Interacting Multiple Model (IMM) approach to estimate the lane pixel positions in the image. Two models are used: one for straight lines and one for curves. The simulation results show that this method has good robustness under various road scenarios.
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KEYWORDS

Lane detection;
Interacting Multiple Model (IMM);
Robustness.

INTRODUCTION

In the past years, active safety systems were increasingly introduced into cars to lower the number of accidents. The U.S. Department of Transportation reported 33, 963 fatalities in the year of 2009; 59% traffic accidents were caused by lane departure[1]. Therefore, road lane detection technology became a hot issue in the intelligent vehicle research at present[2]. A lot of effort in the research area is spent to increase robustness; that is to detect lanes also in case of inhomogeneous lightning conditions, non-straight lanes, or lane occlusion.

Several algorithms for lane detection were introduced. These can be grouped into three categories: edge based methods, parameter space transformation based methods, and model based methods. All these methods have their own limits, as they are usually restricted by one representation of lanes.

Edge based methods are widely used, but highly depend on the methods used to extract the edges corresponding to the lane boundaries; when the road condition is complex and especially in case of lane occlusion the methods may fail[3-5].

Parameter space transformation, such as Hough transformation, is another approach to get the lane information in lane departure systems. A major issue of Hough transformation is the necessity to stick to one particular geometric shape, in the context of lane detection usually a line. Hence the Hough-based transformation algorithm can typically only detect straight lanes.

Model based methods[6] try to map detected features of the image to a model by adapting model parameters. Several models can be defined and the method selects the best-fitting model per lane. However, it is not possible to combine models for one lane and image.

To overcome the identified limitations, this paper suggests using an Interacting Multiple Model (IMM) approach known from the target tracking domain[14]. With this approach, it is possible to fuse the estimations of several models simultaneously to obtain an optimal match of the lane. This leads directly to an increase of robustness.

Our detection algorithm can be divided into two steps: preprocessing phase and a tracking phase for lane identification.

The preprocessing phase consists of four stages. The first stage is based on regions of interest to reduce the image size. In the next step, the image is processed by a median filter to reduce noise and retain the details. Otsu's algorithm is used in the third stage to identify areas that represent potentially markings. Finally image erosion is used to remove outliers.

The tracking is performed in spatial dimension, meaning that it tracks the lane within one frame. Tracking lanes using information of consecutive frames is not the scope of this paper. During tracking two models are used for the IMM approach: one for straight lines and one for curves. Each lane is tracked by an instance of an IMM-based filter.

The algorithm is evaluated using test images from the Carnegie Mellon database. The experiment results indicate that the proposed method achieves precise lane markings information from the video.

The remainder is organized as follows: Sec. II briefly discusses related work. The algorithm is described in the following sections: Sec. III describes the preprocessing phase, Sec. IV the tracking phase. Experimental results are discussed in Sec. V. Finally, the paper is concluded in Sec. VI.

Related work

Jianwei Gong et al.[9] used the edge detection, dynamic windows and Hough transform method to extract the lane information. Most results are good except in small ring roads or blind bend. And the previous position information cannot be used to guide the vehicle when the road lane markings are not very clear.

Shengyan Zhou et al.[10] used the geometrical model and gabor filter to represent the road. According to his paper, the algorithm achieves high accuracy and is robust to the noise and other interferences. However, the modules are fixed and the numbers of modules is limited by real time requirements. So the situation is that the algorithm could not fit well with the road lane if the number of modules is not enough. But if the number of modules is increased the real time requirement could not be satisfied.

compute the likelihood probability through fitting the detected features to model and[7,8] found the extreme value of the energy function to location the lane then the Kalman filter was used for prediction the parameters of the model. These algorithms would be time-consuming because of the iterative operation.

Image preprocessing stage

Image preprocessing stage plays an important role in the lane detection method. The image is first processed in order to reduce processing time. In most scenes, the road region and non-region areas have obvious boundaries, and the road region is mainly in the lower part of the image[11]. We used the ROI (Region of Interest) approach to make the image of the lower part as the main disposed region. In this way, we could satisfy the efficiency and feasibility of the detection method. As shown in Figure 1, the image is divided into

(a) (b)

Figure 1 : Initialization of regions of interest (ROI).

two parts by the ROI.

The image is then processed by a median filter to retain the details and remove the noises. Otsu algorithm can calculate the adaptive threshold and remove the clutters from the grayscale image[12]. Figure 2 shows the segmentation results on the image after using Otsu algorithm.

Figure 2 : Image after median filter and Otsu algorithm.

After the marking region has been extracted, we use a simplified way to search current lane boundaries and extract the lane features from the image. We start searching for lane pixels from the left to the right on each row. Then we search the next pixel from bottom to top in the frame. The pixel is identified as a lane pixel if it is connected by at least three pixels. Figure 3 illustrates the result.

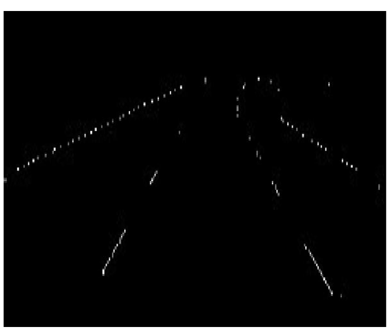

Figure 3 : The result after image processing in the first stage.

Target tracking approach

To distinguish the noise and the lane pixels in the frame, we use the target tracking method to solve this problem. Considering that the lane pixels in the image are the target tracks on 2-D Cartesian coordinate. For example, all the pixels in one lane module can be considered as one target track on the 2-D Cartesian coordinate. Using this method, we do not need to fix the points with the fixed number of modules or to worry about the complex scenes that Hough transform could not get good performances. The only thing we need to do is that just estimate the target (lane pixel) position on the Cartesian coordinate, distinguish the pixels which belong to one target track and the pixels which belong to clutter.

With the images which were processed in the image preprocessing stage, the pixels are considered as the measurement of the target and its coordinate (X, Y) is also considered as the measurement's position. We read the pixels from the bottom line up and in each row form left to right one by one. One important thing is that we consider the measurement's ordinate as its step. For example, if one measurement's position is (13, 56) then we consider this measurement's step as 56.

Track management

Temporary track:

The measurements are added to the set of temporary tracks only after the updates of confirm tracks are finished and unassociated measurements are existed in the previous scan. The set of temporary tracks is initialized by using two point differencing method[13]. Once a temporary track was set up and updated by the measurements at least three times, then we could add the temporary track to the set of confirm tracks.

Confirm track

Each confirmed track represents one target and it is associated with the measurements to update. Besides, two confirmed tracks are merged if the distances of these two tracks in the x and y directions is less than a threshold (such as 5). If the measurements are not associated with the confirmed track in a long time, then we delete the track.

Models Configuration

The target motion model in Cartesian coordinate is

$$\mathbf{x}_{k+1} = \mathbf{F}_k \mathbf{x}_k + \mathbf{\Gamma}_k \mathbf{w}_k \qquad \mathbf{k = 0,1,2...} \tag{1}$$

$$z_{k+1} = Hx_{k+1} + v_{k+1} \tag{2}$$

where $\mathbf{x} = (\mathbf{X}, \dot{\mathbf{X}}, \mathbf{Y}, \dot{\mathbf{Y}})$ denotes the target's state including the position and the velocity. $X, \dot{X}$ are the position and the velocity of the target with respect to x-axis, and $\mathbf{Y}, \dot{\mathbf{Y}}$ are the position and the velocity of the target with respect to y-axis in Cartesian coordinates, and w is the acceleration process noise, $\mathbf{z} = (\mathbf{X}, \mathbf{Y})'$ is the measurement, v is the random measurement noise. Sup-

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pose the target motion is described by two models: Constant velocity model (CV) and constant turn model (CT). Then we could use the IMM approach to estimate each model and combine the results together in order to get the precise estimate of the target.

Constant Velocity (CV) Model:

$$\mathbf{F}=\begin{bmatrix}1&T&0&0\\0&1&0&0\\0&0&1&T\\0&0&0&1\end{bmatrix}\quad \mathbf{\Gamma}=\begin{bmatrix}\frac{T^2}{2}&0\\T&0\\0&\frac{T^2}{2}\\0&T\end{bmatrix} \tag{3}$$

$$\mathbf{H}=\begin{bmatrix}1&0&0&0\\0&0&1&0\end{bmatrix}$$

Constant Turn (CT) Model:

$$\mathbf{F}=\begin{bmatrix}1&\frac{\sin\omega T}{\omega}&0&\frac{-(1-\cos\omega T)}{\omega}\\0&\cos\omega T&0&-\sin\omega T\\0&\frac{(1-\cos\omega T)}{\omega}&1&\frac{\sin\omega T}{\omega}\\0&\sin\omega T&0&\cos\omega T\end{bmatrix} \tag{4}$$

$$\mathbf{\Gamma}=\begin{bmatrix}\frac{T^2}{2}&0\\T&0\\0&\frac{T^2}{2}\\0&T\end{bmatrix}\quad \mathbf{H}=\begin{bmatrix}1&0&0&0\\0&0&1&0\end{bmatrix}$$

where T denotes the discrete sample period and ω is the angular velocity.

Interacting multiple model (IMM)

The IMM algorithm is well known to have good performance with respect to the target maneuvering although it is a sub-optimal filter based on the Markov chain whose transition depends on the latest state. The details content are well explained in[14]. The main elements of the IMM algorithm are as follows:

The mode transition probabilities, which are related to Markov chain, are defined as

$$\pi_{ij}=P\left\{m_{k+1}^{j}\middle|m_{k}^{i}\right\} \tag{5}$$

where m_k^i denotes the event that model matches the system at time k.

Model conditional reinitialization:

Initially, the states from the previous step of each model are mixed mixing weight in the IMM filter. The mixing weight can be written as

$$\mu_{k-1|k-1}^{j|i}=\frac{\pi_{ji}\mu_{k-1}^{j}}{\mu_{k|k-1}^{i}}\qquad i,j=1,2. \tag{6}$$

where μ_{k-1}^{j} is the mode probability of the mode j in the previous step and π_{ji} is the probability for the transition from model j to model i.

$\mu_{k|k-1}^{i}$ is the predicted mode probability

$$\mu_{k|k-1}^{i}=\sum_{j=1}^{2}\pi_{ji}\mu_{k-1}^{j}\qquad i=1,2. \tag{7}$$

The mixing estimate state $\overline{x}_{k-1|k-1}^{i}$ and the mixing covariance $\overline{P}_{k-1|k-1}^{i}$ of the model are

$$\overline{x}_{k-1|k-1}^{i}=\sum_{j=1}^{2}\hat{x}_{k-1|k-1}^{j}\mu_{k-1|k-1}^{j|i}\qquad i=1,2. \tag{8}$$

$$\overline{P}_{k-1|k-1}^{i}=\sum_{j=1}^{2}\mu_{k-1}^{j|i}\Big[P_{k-1|k-1}^{j}+(\overline{x}_{k-1|k-1}^{i}-\hat{x}_{k-1|k-1}^{j})(\overline{x}_{k-1|k-1}^{i}-\hat{x}_{k-1|k-1}^{j})^{T}\Big]\quad i=1,2. \tag{9}$$

where $\hat{\mathbf{x}}_{\mathbf{k-1|k-1}}^{\mathbf{j}}$ and $P_{k-1|k-1}^{j}$ are the state and covariance of the model j of the previous step, respectively.

Model conditional filtering

Using the mixing initial state and covariance of previous process, the KF of each model predicts and updates the model state and covariance.

Predict the state and the covariance matrix

$$\hat{x}_{k|k-1}^{i}=F_{k-1}^{i}\overline{x}_{k-1|k-1}^{i}+\Gamma_{k-1}^{i}w_{k-1}^{i},$$
$$P_{k|k-1}^{i}=F_{k-1}^{i}\overline{P}_{k-1|k-1}^{i}(F_{k-1}^{i})^{T}+\Gamma_{k-1}^{i}Q_{k-1}^{i}(\Gamma_{k-1}^{i})^{T} \tag{10}$$

Compute the kalman gain and the innovation

$$K_{k}^{i}=P_{k|k-1}^{i}H^{T}(S_{k}^{i})^{-1} \tag{11}$$

$$S_{k}^{i}=HP_{k|k-1}^{i}H^{T}+R_{k}^{i} \tag{12}$$

Update estimate with measurement

$$\mathbf{x}^{i}_{k|k} = \mathbf{x}^{i}_{k|k-1} + \mathbf{K}^{i}_{k}\left(\mathbf{z}_{k} - \mathbf{H}\mathbf{x}^{i}_{k|k-1}\right) \tag{13}$$

Update the error covariance

$$P^{i}_{k|k} = P^{i}_{k|k-1} - K^{i}_{k} S^{i}_{k} (K^{i}_{k})^{T} \tag{14}$$

Model probability update:

The likelihood function of each mode i at time k, under the Gaussian assumption, is given by

$$\mathbf{L}^{i}_{k} = \mathbf{P}\left[\hat{\mathbf{z}}^{i}_{k} \middle| \mathbf{m}^{i}_{k}, \mathbf{z}^{k-1} = \mathbf{N}\left(\hat{\mathbf{z}}^{i}_{k}, 0, \mathbf{S}^{i}_{k}\right)\right] \tag{15}$$

where $\tilde{z}^{i}_{k}$ is the measurement residual

$$\tilde{z}^{i}_{|k} = z_{k} - H^{i}_{k}\hat{x}^{i}_{k|k-1} \tag{16}$$

The model probability update is done as follows:

$$\mu^{i}_{k} =_{i} \frac{\mu^{i}_{k|k-1} L^{i}_{k}}{\sum_{j=1}^{2} \mu^{j}_{k|k-1} L^{j}_{k}} \tag{17}$$

Estimation fusion:

According to the Gaussian mixture equation, the combined state $\hat{x}_{k|k}$ and its covariance $P_{k|k}$ are calculated as

$$\hat{\mathbf{x}}_{k|k} = \sum_{i=1}^{2} \boldsymbol{\mu}^{i}_{k} \hat{\mathbf{x}}^{i}_{k|k} \tag{18}$$

$$\mathbf{P}_{k|k} = \sum_{i=1}^{2} \boldsymbol{\mu}^{i}_{k}\left[\mathbf{P}^{i}_{k|k} + \left(\hat{\mathbf{x}}_{k|k} - \mathbf{x}^{i}_{k|k}\right)\left(\hat{\mathbf{x}}_{k|k} - \mathbf{x}^{i}_{k|k}\right)^{T}\right] \tag{19}$$

Experimental results

We test our algorithm under a variety of different road conditions, when there are bend lanes, shadow and vehicle on the road. The test images are from the Carnegie Mellon database.

As shown in Figure 4(a), when a vehicle driving in the straight road which have four lanes, the approach

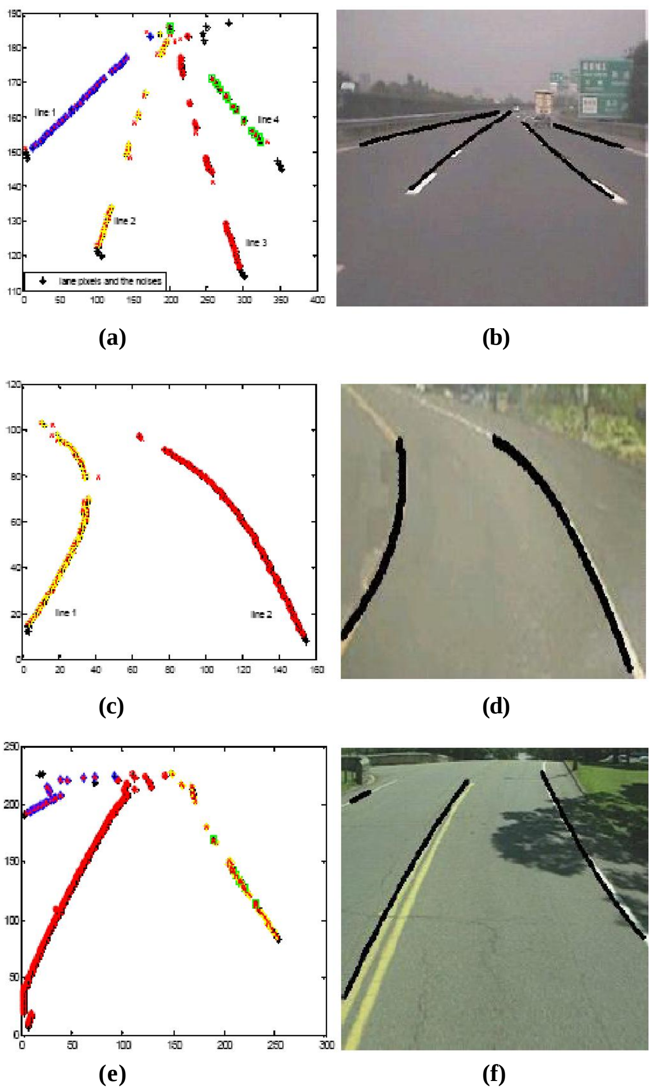

Figure 4 : Lane detection results in single frame

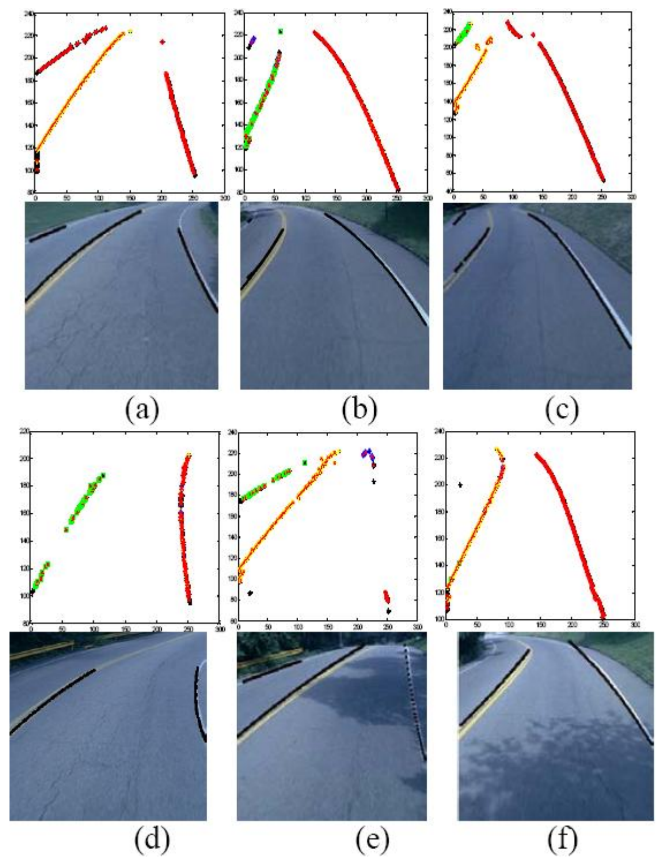

Figure 5 : Lane detection results in consecutive frames

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detects four targets from the image. Each color represents one target's track and the first three pixels were used for track initiation. (b) shows the detection result on video frame. (c) shows the result when there are curve lanes on the road and (d) is the detection result on video frame. (e) and (f) shows the performance under the shadows.

Result in consecutive frames

We tested our algorithm in consecutive frames in video file. Some results are shown in Figure 5.

Figure 5(e) shows the result under the shadow scene. From the above figure, we can see after the image processed stage the right lane has little lane marking information according to the shadows. The traditional method may have poor performance under this situation while our approach can still keep high performance and robustness.

Either from the single frame, or from the consecutive frames, the results show that the algorithm successfully detected road lane even under ill-lighting conditions including shadows.

CONCLUSION

Using visual sensors for lane detection has a great significance for real time vehicle navigation. This paper focuses on this topic and presents a target tracking method to detect the lanes from the image. It can successfully detect bend lanes which Hough transform could not detect, and it can also distinguish the noise and the lane pixels on the image by using target tracking method. That is very important for the system's accuracy and stability effectively. However, there are still many problems to be solved. For example, we record the pixel's ordinate as the step of the measurement. As a matter of fact, it requires that each target should have no more than one measurement at each step, which means that each lane track should have only one measurement on each row of the image. If one lane track is turn right and back towards the bottom on the image. The lane detection algorithm would consider this whole lane track as two lanes by mistake. Follow up work would focus on this problem. Nevertheless, it can still detect the lanes at this situation and there are no special requirements for camera parameters, background models, or any other road surface models. This makes the algorithm more adaptive to various road environments.

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