Annealed Particle Filter Algorithm Used for Lane Detection and Tracking

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***Abstract*—This paper describes a lane detection and tracking method based on annealed particle filter algorithm, which combines multiple cues with annealed particle filter. As a first step, preprocessing, with bar filter and color cues being used. In the annealed particle filter step, angle information of edge map is utilized to measure weights of particles. Experiments show that the time cost of annealed particle filter algorithm for each frame is largely reduced comparing with the lane detection and tracking using conventional particle filter algorithm, which is the main contribution of this paper. Furthermore, on this basis, we build a robust lane model which can be applied to not only the linear road but also the curved road. The experiments indicate that it is effective for lane detection and tracking.**

***Index Terms*—lane detection and tracking, multiple cues, annealed particle filter, robust lane model.**

I. Introduction

People have a growing interest for driver assistant systems that are used to monitor the driving conditions by visual technique, and warn and guide drivers the road conditions. Lane marker is one of the most important road signs, which makes lane detection a necessary part for driver assistant system and unmanned vehicle.

For several decades, lane detection and tracking have been widely studied for driving on a highway [1], [2] or urban road [3], for single [1], [4] or multiple [5], [6] lanes. Various shape models have been applied to describe borders of a lane.

In this paper we describes a robust lane tracking algorithm based on annealed particle filter, which combines multiple cues with annealed particle filter. As a first step, preprocessing, with bar filter and color cue being used. The multiple cues contain bar filter and color cue. Bar filter is efficient to detect bar-shape objects like road lane, and as the color of the lane on the road is mostly yellow or white, we constrain a rough range of the color in the image. Both bar filter and color cue are used to filter out noises, and to speed up the whole program. In the annealed particle filter step, angle information of edge map is utilized to measure weights of particles, the details are described in Section III. The experiments show that the particles number and the time cost per frame of the method are largely reduced compared with the method based on conventional particle filter, which is the main contribution of this paper. For better detecting and tracking lanes using the method in this paper, we also build a robust lane model which can be applied to detect and track the lanes of not only the linear road but also the curved road. The test results show that it is effective.

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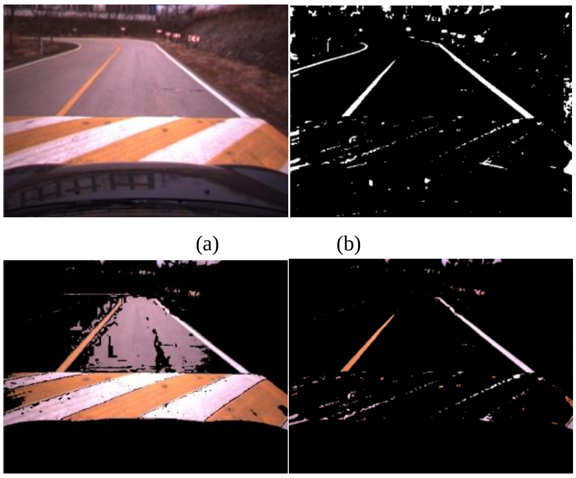
II. Processing-Multiple Cues

In the preprocessing step, multiple cues, including bar filter and the color cue, are processed separately before using annealed particle filter (show in Fig.1(d)).



(a) (b)

(c) (d)

Figure. 1. Multiple cues. (a) Original image; (b) Bar filter; (c) Color cue; (d) Preprocessing result.

A. Bar Filter

Lane marker is a relatively distinctive feature, which can be described as a black-white-black bar-like object [7], [8]. The bar filter is implemented by checking pixels that satisfies the black-white-black condition based on intensity image (as shown in Fig.1 (b)). As the direction of lane is vertical, the bar filter is executed on the horizontal direction. The *i-th* pixel of the image after bar filter processing is defined as:

$$BarFilt[i] = (Inten[i] - Inten[i + BarW]) + (Inten[i] - Inten[i - BarW]) \tag{1}$$

where *BarW* is a width predefined, here we use 15 pixels, and $i \pm BarW$ means a pixel shifted a length of *BarW* on the horizontal direction.

B. Color Cue

In order to better distinguish colors of lane marker and other colors, we first convert RGB images into HSV color space. Based on HSV color space two loose conditions are

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defined to limit the color of the input images to the white zone and yellow zone [8] (shown in Fig.1(c)).

$$Hue(i,j) < \alpha; Value(i,j) > \beta \tag{2}$$

where *Hue(i, j)* is the hue of pixel (i, j) and *Value(i, j)* is the value of pixel (i, j) in HSV color space and the total range of both *Hue* and *Value* are [0,1]. Two values of α, β are 0.95 and 0.6 separately.

III. Annealed Particle Filter

The annealed particle filter (APF) [9] is a sampling method to approximate distributions by a set of samples, and it is tracking the state of the system. The APF is similar to a conventional particle filter but instead of a single factored sampling step, it has an annealing run at each frame in the video sequence. An annealing run at each layer is the implementation of a conventional particle filter. In this paper, we use a stationary motion model in the annealed particle filter algorithm. The particles moved to the positions with high probability. In the correction step, the angle information of edge map is used to measure the weights of particles.

A. Importance Sampling

The set of samples is expressed in (3), where the state of one sample s_i is associated with one weight π_i. The importance sampling procedure selects samples from this set such that samples with higher weights are more likely to be drawn.

$$S_t = \{(s_i, \pi_i)\}, i = 1,2,\ldots,N, \sum_{i=1}^{N} \pi_i = 1 \tag{3}$$

B. Measurement of Particles

Measurement of particles evaluates the likelihood of how well the samples fit a new observation. Observation in this work is the angle information of edge map in current image. Edge map is obtained through processing the original image by Sobel mask, where edge direction (in (4)) and magnitude (in (5)) of the whole image can be obtained.

$$\theta = \arg\tan\left(\frac{I_y}{I_x}\right) \tag{4}$$

$$A = \sqrt{I_x^{\,2} + I_y^{\,2}} \tag{5}$$

The state space of particles is R^2, constituted by the X-coordinate of the center point of side lanes and the distance from the center point to one side lane. Y-coordinate of the center point is fixed at the middle of the whole image. One sample is denoted by $s_i = (x_i, d_i)$. Two small regions of one sample are extracted with the center of $(x_i - d_i, y)$ and $(x_i + d_i, y)$ (as shown in the left upper image of Fig.2). The width and height of these two small regions are fixed at 51. The whole region of direction is divided into 9 ranges, as shown in (6).

$$bins = \{-90, -70, -50, -30, -10, 10, 30, 50, 70, 90\} \tag{6}$$

It counts directions of points in these two small regions that fall between the elements in the bins. The increment of voting value is the edge magnitude of the current voting point. The voting results of the points in left and right small regions (right upper image of Fig.2) are shown in the right middle figure and right bottom figure of Fig.2, respectively. The average direction of the range corresponding to maximum magnitude of all bins is used to represent the small region.

The sample with a value of zero for the addition of the direction of left small region and right small region has a high possibility to be lane marker because the lanes of the two sides are mostly symmetric. We model the weights of particles by Gaussian distribution with (μ, σ). We set μ, σ to 0 and 30, respectively, according to our experiments (as shown in the left bottom figure of Fig.2).

$$w_i = e^{\frac{-(add_i - \mu)^2}{2\sigma^2}} \tag{7}$$

where add_i is the addition of the direction of the left small region and the right small region for one sample, w_i is the weight of this sample.

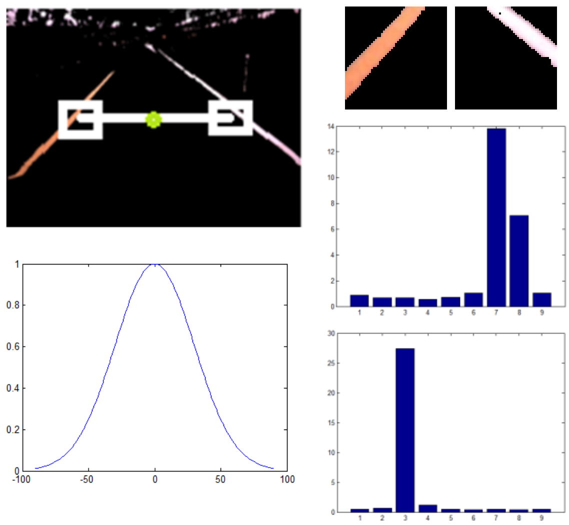

Figure.2. Measurement of particles. Left upper: image with one sample and its two small regions; Left bottom: modeling of weights of particles; Right upper: two small regions for one sample; Right middle: voting result for left small region; Right bottom: voting result for right small region.

C. Annealed Particle Filter

Tracking systems that use conventional particle filter can get distracted by local features of the posterior density which reduces their accuracy. Deutscher et al. [9] and Davidson et al. [10] approached this problem by applying simulated annealing optimization techniques. They referred to their solution as the annealed particle filter. The goal here is to modify the particle filter such that the number of needed particles is drastically reduced and the particles do not congregate around local maximum. The key idea is to gradually introduce the influence of narrow peaks in the weighting function $w(y_t, x_t)$. This is achieved by starting a search run in successive layers gradually change the weighting function as

$$w_m(y_t, x_t) = w(y_t, x_t)^{\beta_m} \quad (8)$$

for $\beta_0 \rangle \beta_1 \rangle \cdots \rangle \beta_M$.

The steps involved in each annealing run are illustrated in Fig.3

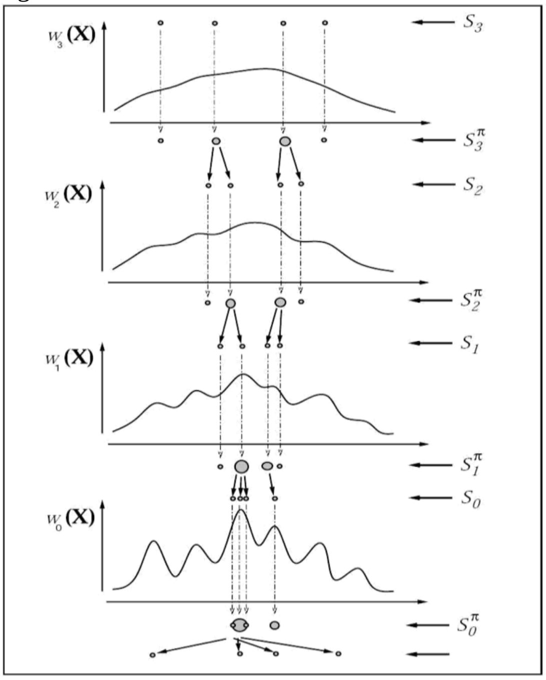

Figure. 3. An illustration of an annealing run for M=3. It shows the variation of the weighting function, and the re-sampling and diffusion steps. The influence of the peaks is gradually introduced into the weighting function w_m . Consequently, the particles converge at the global maximum in the last layer w_0 and do not get trapped in local maximum peaks as opposed to the standard particle filter [9].

Annealed particle filter procedure in our work mainly has three steps including re-sampling, correction and weight normalization.

The main cycle consists of repeated calling of annealed particle filter procedure. The flow chart of the whole system is shown in Fig.4.

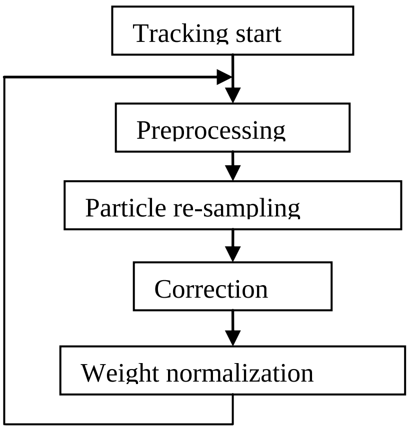

Figure. 4. Flow Chart of the whole system.

IV. Robust Lane Model

For making the lane detection and tracking more robust, we build a robust lane model on the base of the lane detection and tracking method in this paper, it can be applied to detect and track the lane of not only the linear road but also the curved road. It is illustrated in Fig.5, the down line and up line are fixed at some positions in y coordinate, we use the annealed particle filter algorithm to detect and track the down line and up line separately, the degree of freedom of the model can be regarded as 4.

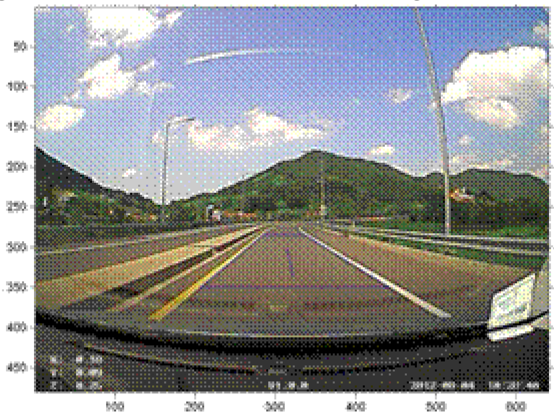

Figure. 5. The robust lane model built in this paper.

V. Experimental Results

In our work, we use 20 and 80 particles (N=20, N=80) and 3 annealed layers (M=3) to test the program separately. The test results are shown in Fig.6,7. The experimental results are described in Section A. Furthermore, the time performance is illustrated in Section B.

The robust lane model, which has been stated in Section IV, is tested in a curved road situation. The experimental result is shown in Fig.8. The particle number is set to 80 (N=80) and the annealed layer number is set to 5 (M=5) in the experiment. The test result is described in Section C.

A. Experimental Result

The experiment situation is the dashed lane maker situation. This situation is very challenging as the lane marker is cut in and out. As the result indicates, the dashed line is well tracked. One reason is that the particles cannot abruptly vary because of the vanishment of the dashed line, and the other reason is that our observation is based on a small region, which makes the dashed line to be observed rapidly as dashed lane disappears regularly. Fig.6,7 are the experimental results of the lane detection and tracking using annealed particle filter, where the particle number is 20 (N=20) and annealed layer number is 3 (M=3) in Fig.7, the particle number is 80 (N=80) and annealed layer number is 3 (M=3) in Fig.8.

B. Time Performance

We list the time cost of conventional particle filter algorithm and annealed particle filter algorithm for lane detection and tracking in Table I. The test image size is 640*480. The two methods have the similar tracking result, but the used particle number and the time cost per frame of the method based on annealed particle filter are both largely reduced compared with the method based on conventional particle filter, which is the main contribution of this paper.

Figure. 6. Experimental results. The particle number is 20 (N=20), the annealed layer number is 3 (M=3).

TABLE I. TIME COST PER FRAME CONTRAST OF CONVENTIONAL PF ALGORITHM AND APF ALGORITHM (SECONDS)

Algorithm	Time cost per frame(seconds)
PF(N=1000)	0.15
APF(M=3,N=20)	0.028
APF(M=3,N=80)	0.053

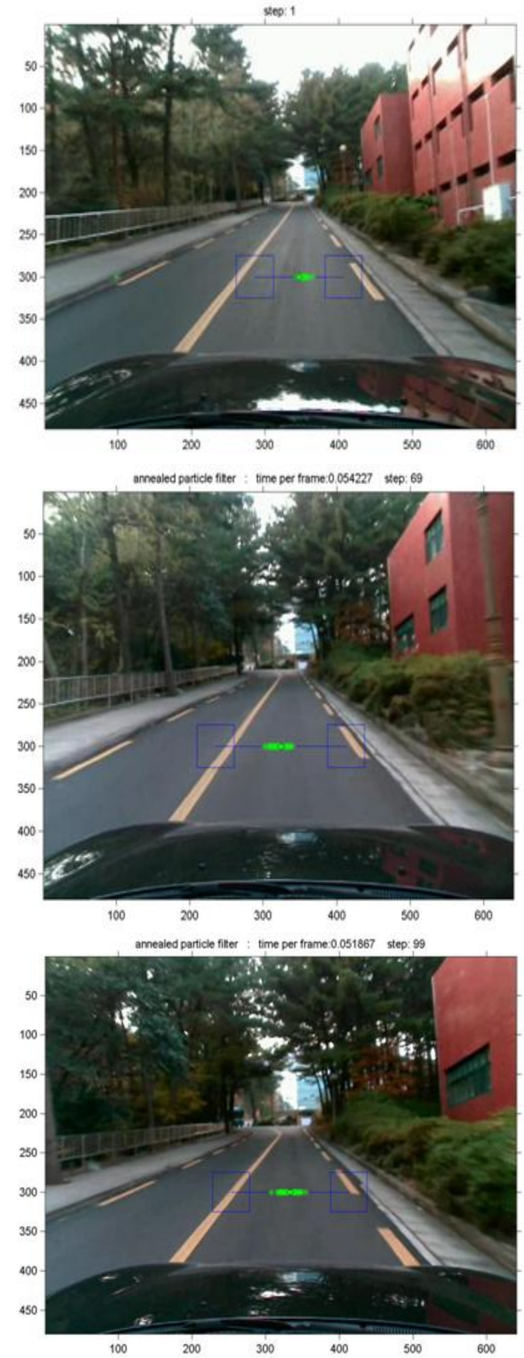

Figure. 7. Experimental results. The particle number is 80 (N=80), the annealed layer number is 3(M=3).

C. Experimental Result of Robust Lane Model

The experiment situation is the curved road situation, we use 80 particles (*N*=80) and 5 (*M*=5) annealed layers to test the program. The test result shown in Fig.8 indicates that the lane of curved road is well tracked using the model illustrated in Section 4. The time performance is listed in Table II. The test image size is 640*480.

TABLE II. TIME COST PER FRAME OF APF ALGORITHM FOR CURVED ROAD TRACKING

Algorithm	Time cost per frame(seconds)
APF(M=5,N=80)	0.074

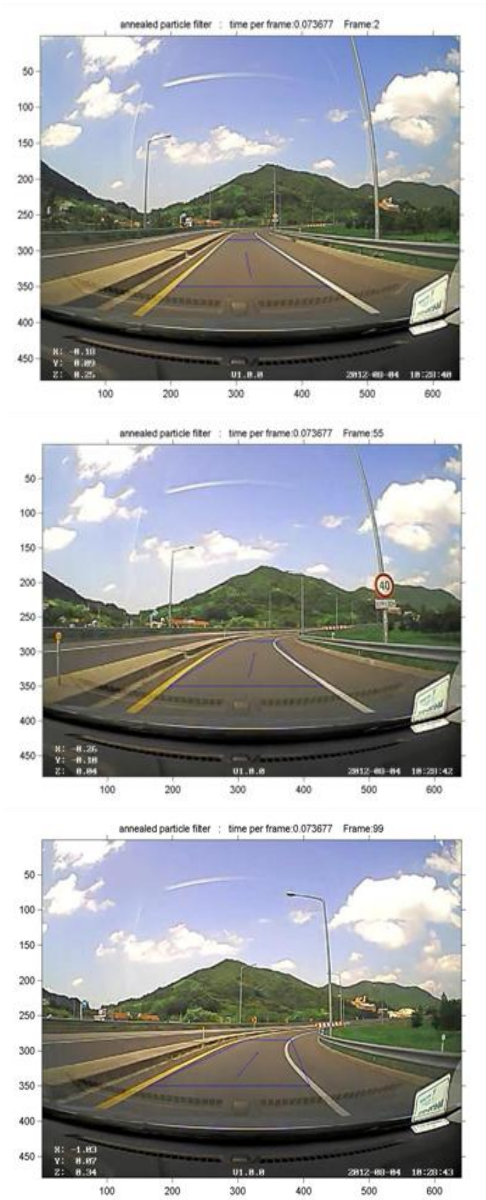

Figure. 8. Experimental results. Lane detection and tracking using the robust lane model for curved road, the particle number is 80 (N=80), the annealed layer number is 5 (M=5)

VI. CONCLUSIONS

A lane tracking approach has been presented by combining multiple cues with annealed particle filter in this paper. The multiple cues including bar filter and color cue are processed in the preprocessing step. After that, annealed particle filter is exploited to track the lane marker, the time cost per frame is reduced a lot comparing with the method based on conventional particle filter. The robust lane model built on this basis is effective to detect and track the lane of both the linear road and the curved road.

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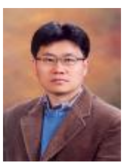

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