Robust Vision based Lane Tracking using Multiple Cues and Particle Filtering 1

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Abstract

One of the more startling effects of road related accidents is the economic and social burden they cause. Between 750,000 and 880,000 people died globally in road related accidents in 1999 alone, with an estimated cost of US$518 billion [11]. One way of combating this problem is to develop Intelligent Vehicles that are self-aware and act to increase the safety of the transportation system. This paper presents the development and application of a novel multiple-cue visual lane tracking system for research into Intelligent Vehicles (IV). Particle filtering and cue fusion technologies form the basis of the lane tracking system which robustly handles several of the problems faced by previous lane tracking systems such as shadows on the road, unreliable lane markings, dramatic lighting changes and discontinuous changes in road characteristics and types. Experimental results of the lane tracking system running at 15Hz will be discussed, focusing on the particle filter and cue fusion technology used.

1 Introduction

It is estimated that around 30% of fatal car crashes can be attributed to driver inattention and fatigue [10, 20]. Numerous studies have been performed to analyze signs of driver fatigue through the measurement of the visual demand on the driver, but few have also considered the environment external to the vehicle. An Intelligent Transportation Systems (ITS) project has recently been initiated at The Australian National University (ANU) which is focused on autonomous driver monitoring and autonomous vehicle control to aid the driver [8]. A major aim of this project is the development of a system of cooperating internal and external vehicle sensors to aid research into the visual behavior of the driver [2]. This paper presents the first results from this study, where a lane tracker was developed using particle filtering and visual cue fusion technology.

2 The Experimental Platform

The testbed vehicle, TREV (Transport Research Experimental Vehicle), is a 1999 Toyota Landcruiser 4WD (Figure 2).

Figure 1 defines the problem solved by this lane tracker including the localization and tracking of the road with respect to the vehicle (the lateral offset of the vehicle (y) and the yaw of the vehicle (φ) with respect to the centreline of the road) and the determination of the road width (rw).

Figure 1: The vehicle state and road width tracking state space. $O_{nir}$, $O_{cer}$, $L_{start}$ and $L_{end}$ define the different regions used by the cues described in Section 3.1.1. Note that this picture is exaggerated for clarity.

Figure 2: TREV - the testbed vehicle.
As vision is the main form of sensing in this project, two different vision platforms have been installed (Figure 3). The first vision platform consists of a passive set of cameras mounted on the dashboard, which are part of the faceLAB™ [20] system for driver monitoring. The second vision platform, CeDAR, is an active vision head designed at ANU [17] and carries two cameras that are configured for dual near-field and far-field scene coverage. The near-field camera on CeDAR, the main form of sensing for the lane tracker, was used passively at 60Hz with a field of view of 46.4°.

Figure 3: The vision platforms in TREV. Top: CeDAR active vision head. Right (above the steering wheel): faceLAB™ passive stereo cameras.

3 Lane Tracking

Despite many impressive results from single cue lane trackers in the past [4, 7, 15, 18, 19], it is clear that no single cue can perform reliably in all situations.

Dickmanns [7] pioneered the 4D approach to lane tracking in the PROMETHEUS project where they demonstrated autonomous control of their VaMoRs vehicle at speeds up to 100 kph on the German Autobahn. A detailed dynamical model of the vehicle was used with edge based feature detectors to localise and track the road over time. However, the system was sensitive to dramatic changes in illumination and shadows across the road since edge based feature detection was the primary means of lane extraction. The General Obstacle and Lane Detection system (GOLD [4]) used in the ARGO vehicle at the University of Parma transforms stereo image pairs into a common bird’s eye view and uses a pattern matching technique to detect lane markings on the road. This system is limited to roads with lane markings as they form the very basis of the search method. The NAVLAB project at Carnegie Mellon University [19] has explored many different lane detection algorithms. SCARF [6] used adaptive color classification and a voting scheme for lane localization, while YARF [13] extended this with the addition of feature detection. ALVINN [3] employed a neural net to learn a function from image space to steering angle through supervised training. MANIAC [12] extended ALVINN through a modular architecture that used pre-trained ALVINN networks for different road types. RALPH [15] validates multiple hypotheses of the road curvature by removing the hypothesized curvature from a bird’s eye view of the road and condensing the rows of this image into single row. Correct hypotheses will form a clear peak and trough in the intensity signal that can be compared with predetermined templates to discover the lateral offset of the vehicle. The system adapts to new road types through the use of a number of predetermined templates and a rapidly adapting template it calculates using the far-field view of the road.

A common characteristic of all of these systems is that they rely on only one or two cues for lane detection that are used regardless of how well they are performing. No attempt is made to seamlessly track the road as its characteristics change (i.e. from a highly structured highway to semi-structured lanes to unstructured off-road conditions) at a fundamental level of the algorithm. In contrast with the CMU systems that accommodate changes in road appearance by switching pre-trained or retrained models, our system is based on the Distillation Algorithm that attempts to dynamically allocate computational resources over a suite of cues to robustly track the road in a variety of situations. This is also the first use of particle filtering in a road vehicle application. A brief summary of the Distillation Algorithm appears below, however for a detailed discussion of the algorithm, see [1, 2].

3.1 The Distillation Algorithm

The Distillation Algorithm is a novel method for target detection and tracking that combines a particle filter1 with a cue fusion engine and is suitable for both low and moderately high dimensional problems. Figure 3.1 shows the different steps in the Distillation Algorithm.

The algorithm is based in Bayesian statistics and is self-optimized using the Kullback-Leibler distance to produce the best statistical result given the computational resources available. The basis of the Distillation Algorithm, is that a suite of cues are calculated from image and state information and combined to provide evidence strengthening or attenuating the belief in each hypothesis of the particle filter. The utility2 of each cue

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1. A particle filter [5] is a search method that represents the continuous posterior density with a set of discrete particles, or hypotheses. These particles represent the target location and are moved to positions of high probability to concentrate computational power in those areas of interest.

2. Cues are allocated CPU time based on their performance
over time is evaluated and the set of cues that are performing optimally are distilled to a select set that can run in the foreground at a desired processing speed. The remainder of the cues are processed in the background at speeds less than the desired frequency and their results are monitored for a contribution to the overall tracking. The cues can be reinstated to run in the foreground at any time if their contribution will result in improved tracking performance.

3.1.1 Lane Tracking Cues: Each cue is specifically developed to work independently from the other cues and is customized to perform well for different scenarios (i.e. edge based lane marker tracking, color based road tracking, etc.) while being designed to be simple and efficient. Individually, the cues would perform poorly, but when they are combined through the cue fusion process, they produce a robust solution to lane tracking.

Two different classes of cues are used in the lane tracker. Image based cues use the camera image stream as the observation measurements. State based cues use the state in each particle as the observation measurement. These were introduced as a heuristic to control the result from the lane tracker (see Section 4.3). The first four cues below are image based while the last two are state based.

The Lane Marker Cue is suited for detecting roads that have lane markings. An approximation to a 1D Laplace of Gaussian (LoG) kernel is horizontally correlated with an intensity image of the road to emphasize vertical “bar” like features. Figure 5 shows the sensor model evaluation process.

The Road Edge Cue is suited to roads with lane markings or defined edges. It uses a Canny edge map to highlight road boundaries and lane marker edges. Figure 6 shows the sensor model evaluation process.

The Road Color Cue is useful for any roads that have a different color than their surroundings (both unmarked and marked roads). It returns the average pixel value in the hypothesized road region from a road color probability map, which is dynamically generated each iteration using the estimated road parameters and the YUV color image from the previous iteration.

The Non Road Color Cue is used to evaluate non-road regions in the road color probability map described above. It tests that the area just outside of the road region of each hypothesis lie in regions of low road color probability.

The Road Width Cue is useful on multi-lane roads.
where it is possible for the other cues to detect two or more lanes as one. It returns a value from a Gaussian function centered at a desired road width, given the hypothesized road width. The desired road width used in this cue was 3.6 m which was empirically determined from previous lane tracking experiments to be the average road width. The standard deviation of the Gaussian function can be used to control the sensitivity of this cue to varying road widths.

The Elastic Lane Cue is used to move particles towards the lane that the vehicle is in. It returns 1 if the lateral offset of the vehicle is less than half of the road width and 0.5 otherwise. The need for this cue arose when it was discovered that the lane tracking system often switched between lanes when driving on a multi-lane highway. To remove the need to incorporate this step in higher level logic and to keep the particles in locations close to the lane of interest, this cue was introduced to favor particles that described lanes that the vehicle was in.

### 4 Experimental Results

The performance of the system was demonstrated tracking the road in a variety of scenarios that were designed to test the ability of the Distillation Algorithm as a lane tracking solution. Videos of the tracking results can be viewed online at [www.syseng.anu.edu.au/rsl/rsl_demos.html](http://www.syseng.anu.edu.au/rsl/rsl_demos.html).

#### 4.1 Lane Detection

One of the most impressive characteristics of the particle filter is its proficiency for target detection. While many methods have separate procedures for bootstrapping the tracking process, the particle filter seamlessly moves from detection to tracking without any additional computation required for the detection phase. Figure 8 shows the particle locations for the first eight iterations of the lane tracker. The convergence of the mean of the particles to the location of the road takes approximately five iterations while the best estimate of the road location is found within two iterations. The best estimate is the particle that has the highest probability in the pdf.

#### 4.2 Cue Scheduling

Typical behavior of the cue scheduling algorithm is presented in Figure 9. In this case, the two color cues are scheduled into the foreground at iteration 1920, while the Lane Edge Cue is scheduled into the background. This occurs because the combined utility of the two color cues increases to a value greater than the Lane Edge Cue at iteration 1919. The utility of the color cues increased at iteration 1919 because the color at the edge of the road became more distinct from the non-road regions causing the probability density function (pdf) computed by the color cues to approach the pdf of the fused results. All 3 are not scheduled to run in the foreground due to the limited processing power available (managed by cue processor of the Distillation Algorithm).

#### 4.3 Lane Tracking Performance

The lane tracker was tested in several different scenarios including: highway driving with light traffic; outer city driving with high curvature roads; and inner city driving with moderate levels of traffic. Figure 10 shows example output of the lane tracker in the above scenarios using the 6 different cues. The lane tracker was found to work robustly with respect to the problems typically associated with lane tracking including (refer to Figure 10): dramatic lighting changes (A); changes in road color (D-F); shadows across the road (C,G-H); roads with miscellaneous lines that are not lane markings (I); and lane markings that disappear and reappear. This can be attributed to the combination of particle filtering and cue fusion. Because of the particle filter, cues only have to validate a hypothesis and do not have to search for the road. This indirectly incorporates a number of a priori constraints into the system such as road edges meeting at the vanishing point in image space and the edges lying in the road.
Figure 9: The utility of the two color cues increases between iterations 1920 and 1945 and they are both scheduled into the foreground cue list, while the Lane Edge Cue is removed. The total utility over this range has increased as two cues are in the foreground instead of one.

plane. These constraints are often incorporated explicitly into systems to improve performance or which are central to their search method [18].

Figure 10: Results from the lane tracker. The boxes indicate the ends of the lines that define the lane being tracked.

Table 1 outlines the performance of the lane tracking system using a baseline determined by a human operator, hand selecting lane locations. If the best estimate error is greater than a threshold that is based on the lane types and lane markers being tracked, then the iteration was deemed to be a failure. The threshold parameters for this experiment were 0.4 m, 0.04 rad and 0.6 m for the lateral offset (y), yaw (ϕ) and road width (rw) respectively.

The estimates obtained here are the particles with the highest probability from the pdf in the Distillation Algorithm. Selecting a particle from the pdf of the Distillation Algorithm as the best estimate to the target location will naturally produce a result that is not smooth over time as the pdf is discrete. This, combined with randomly sampled particles producing outliers, results in irregular tracking and a lower success rate than is possible. To address this issue, various filtering techniques could be used reduce the error rate and smooth the result obtained in this manner. Median filtering could remove the outliers produced by the randomly sampled particles while a simple moving average filter would smooth the result and be suitable considering the continuous nature of road segments. Another alternative is to use a weighted mean of the sampled pdf as the best estimate.

4.3.1 Cue Fusion: Cue fusion was found to dramatically increase the robustness of the algorithm due to the variety of conditions the cues were suited to. The initial set of cues were limited to the image based cues (Lane Marker, Road Edge, Road Color and Non-Road Color Cues), which contained no prior information except for a transformation between a particle and its road model in image space. Using the initial cues the particle filter often converged to lane segments that the vehicle was not in or to the whole road instead of a single lane. This was due to the lane markings and edges of the road having stronger signals in the observations than the lane markings separating the lanes. The addition of the two heuristic cues (Road Width Cue and Elastic Lane Cue) to strengthen hypotheses that contain the vehicle and have a road width close to the average was found to be a satisfactory solution to this problem.

Table 1: Success rate and mean error performance measures of the lane tracking system for two test cases.

<table>
<thead>
<tr>
<th>Measure</th>
<th>High curvature road</th>
<th>Highway</th>
</tr>
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<tbody>
<tr>
<td>Success (%)</td>
<td>87.6</td>
<td>86.3</td>
</tr>
<tr>
<td>(&lt;y_{err}&gt;(m))</td>
<td>0.13</td>
<td>0.11</td>
</tr>
<tr>
<td>(&lt;\phi_{err}&gt;(rad))</td>
<td>0.02</td>
<td>0.01</td>
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<tr>
<td>(&lt;rw_{err}&gt;(m))</td>
<td>0.10</td>
<td>0.22</td>
</tr>
</tbody>
</table>

4The best estimate error is calculated for each parameter of the particle filter to be the difference between the best estimate and the hand calculated lane parameters.
5 Conclusions

A novel approach to lane tracking has been presented that uses the Distillation Algorithm to track the vehicle pose with respect to the road and determine the road width. It was found that the system benefited greatly from the cue fusion and particle filtering technologies used and was shown to perform robustly in a number of situations that are often difficult for lane trackers. Basic improvements in the selection of the target estimate from the discrete pdf in the Distillation Algorithm have been suggested to improve the accuracy of the system.

The lane tracking system has been successfully used in a number of applications including integrated driver monitoring and lane tracking systems [2] and driver assistance system (see the companion paper by Fletcher et al. [9] and [14]). Future work for the lane tracker includes the integration of horizontal and vertical curvature tracking using CeDAR to actively track the curves of the road.

References


