Springrobot: A Prototype Autonomous Vehicle and Its Algorithms for Lane Detection

Qing Li, Nanning Zheng, *Senior Member, IEEE*, and Hong Cheng

***Abstract*—This paper presents the current status of the Springrobot autonomous vehicle project, whose main objective is to develop a safety-warning and driver-assistance system and an automatic pilot for rural and urban traffic environments. This system uses a high precise digital map and a combination of various sensors. The architecture and strategy for the system are briefly described and the details of lane-marking detection algorithms are presented. The R and G channels of the color image are used to form graylevel images. The size of the resulting gray image is reduced and the Sobel operator with a very low threshold is used to get a grayscale edge image. In the adaptive randomized Hough transform, pixels of the gray-edge image are sampled randomly according to their weights corresponding to their gradient magnitudes. The three-dimensional (3-D) parametric space of the curve is reduced to the two-dimensional (2-D) and the one-dimensional (1-D) space. The paired parameters in two dimensions are estimated by gradient directions and the last parameter in one dimension is used to verify the estimated parameters by histogram. The parameters are determined coarsely and quantization accuracy is increased relatively by a multiresolution strategy. Experimental results in different road scene and a comparison with other methods have proven the validity of the proposed method.**

***Index Terms*—Autonomous vehicle, lane-boundary detection, machine learning, randomized Hough transform (HT).**

I. Introduction

AUTOMATIC vehicle driving aims at automating (entirely or in part) various driving tasks. The tasks of automatically driven vehicles include road following and keeping within the correct lane, maintaining a safe distance between vehicles, regulating the speed of a vehicle according to traffic conditions and road characteristics, moving across lanes in order to overtake vehicles and avoid obstacles, searching for the correct and shortest route to a destination, and driving and parking within urban environments [1].

The field of intelligent vehicles is growing rapidly in the world, in terms of both the diversity of emerging applications and the levels of interest among traditional players in the automotive, truck, public transportation, industrial, and military communities. Intelligent vehicle (IV) systems offer the potential for significant enhancements in safety and operational efficiency. As one component of intelligent transportation systems (ITS), IV systems understand the surrounding environment by a different sensor combined with an intelligent algorithm in order to either assist the driver in vehicle operations (driver assistance) or fully control the vehicle (automation) [2].

For solving the problem of traffic congestion and accidents, especially in big cities such as Beijing, Shanghai, and Guangzhou, the Chinese government has been increasing funding for improving the traffic infrastructure, enforcing traffic laws, and educating drivers about traffic regulation. In addition, research institutes have launched research and development projects in driver assistance and safety warning systems [3].

The Institute of Artificial Intelligence and Robotics, Xi'an Jiaotong University, Xi'an, China, is developing an autonomous vehicle called Springrobot. The research mainly covers the basic vehicular dynamic behaviors, the vehicular sensory technology and in-vehicle data communication, signal processing and the design of information fusion for monitoring running conditions and vehicle–road interactions, the driver-assistance and safety-warning systems, and full control of the vehicle and mobile-agent technology.

As one of the intelligent functionalities, lane detection is the problem of locating lane boundaries. Up to until the present, various vision-based lane-detection algorithms have been developed. They usually utilized different lane patterns (solid or dashed white painted line, etc.) or different road models [two-dimensional (2-D) or three-dimensional (3-D), straight or curved], and different techniques (Hough, template matching, neural networks, etc.).

There has been a significant development of research on machine vision for road vehicles [4] and the lane-boundary detection has been an active research area over the last decade. An automatic lane detector should be able to handle both straight and curved lane boundaries, the full range of the lane markings (either single or double and solid or broken), and pavement edges under a variety of types, lane structures, weather conditions, shadows, puddle, stain, and highlight.

Many systems of lane-boundary detection have been reported in [5] and [6]. In [7], the authors proposed a B-Snake-based lane-detection and tracking algorithm without any cameras' parameters. The B-Snake-based lane model is able to describe a wider range of lane structures, since B-Spline can form any arbitrary shape by a set of control points. The problems of detecting both sides of lane markings (or boundaries) have been merged as the problem of detecting the midline of the lane, by using the knowledge of the perspective parallel lines. The Canny/Hough Estimation of Vanishing Points (CHEVP) is presented for providing a good initial position for the B-Snake and minimum mean-square error (mmse) is proposed to determine

Manuscript received November 30, 2003; revised July 15, 2004 and August 3, 2004. This work was supported by the National Natural Science Foundation of China under Grant 60205001 and Grant 60021302 and the "211" Key Subject Foundation, Xi'an Jiaotong University. The Associate Editor for this paper was S. Tang.

The authors are with the Institute of Artificial Intelligence and Robotics, Xi'an Jiaotong University, Xi'an 710049, China (e-mail: qli@aiar.xjtu.edu.cn; nnzheng@mail.xjtu.edu.cn; hcheng@aiar.xjtu.edu.cn).

Digital Object Identifier 10.1109/TITS.2004.838220

the control points of the B-Snake model by the overall image forces on two sides of lane. In [8], the authors used starting position, direction, and its graylevel intensity features to obtain a lane vector via simple image processing. Out of the many possible lane-boundary candidates, the best one is then chosen as the one at a minimum distance from the previous lane vector according to a weighted distance metric in which each feature is assigned a different weight. An evolutionary algorithm then finds the optimal weights for combination of the three features that minimize the rate of detection error. In [9], authors proposed a method for lane detection using steerable filters to provide robustness to illumination changes and shadows and perform well in picking out both circular reflector road markings, as well as painted line road markings. The filter results are then processed to eliminate outliers based on the expected road geometry and are used to update a road and vehicular model along with the data taken internally from the vehicle. A deformable template and genetic algorithm-based road-recognition algorithm is presented in [10]. The road image was processed with an edge operator to get the edge information and a deformable model was constructed. Then, a genetic algorithm is used to search the global maxima of the likelihood function to get the optimal parameters of the deformable template model of road contour. Reference [11] presented a method to find the lane boundaries by combining a local line-extraction method and dynamic programming. The line extractor obtains an initial position of road lane boundaries from the noisy edge fragments. Then, dynamic programming improves the initial approximation to an accurate configuration of lane boundaries. The input image frame is divided into subregions along the vertical direction. The local line extractor extracts candidate lines of road lanes in the subregion. Most prominent lines are found among candidate lines by dynamic programming that minimizes the function that measures the deviation from a virtual straight line. The search framework based on the dynamic programming (DP) method reduces computational cost. A Hough-transform-based technique for the automated detection and tracking of road contours on high-speed (i.e., low-curvature) roads is presented in [12]. The road contours of the current lane in the near field of view are automatically detected and tracked. Parameter space search optimizations and tracking strategies are outlined. Reference [13] proposed a novel image-processing algorithm to recognize the lane curve of a structured road. The proposed algorithm uses a lane-curve function (LCF) obtained by the transformation of the defined parabolic function on the world coordinates into the image coordinates and needed no transformation of the image pixels into the world coordinates. The main idea of the algorithm is to search for the best described LCF of the lane curve in an image. In advance, several LCFs are assumed by changing the curvature. Then, the comparison is carried out between the slope of an assumed LCF and the phase angle of the edge pixels in the lane region of interest constructed by the assumed LCF. The LCF with the minimum difference in the comparison becomes the true LCF corresponding to the lane curve.

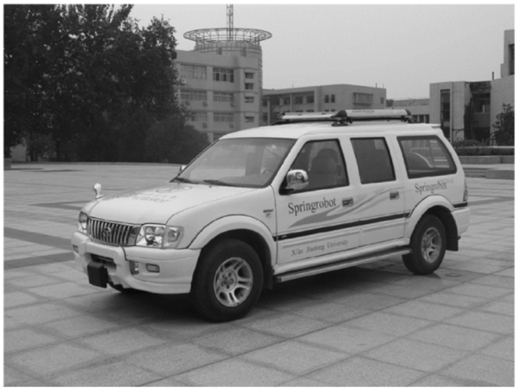


Fig. 1. Springrobot: prototype autonomous vehicle.

Most of the usual lane-markings detection algorithms rely on local image information (edges, pixel gray levels) and often fail if the initialization is performed too far away from the expected solution. Some lane-detection algorithms required the operator to provide the initial estimate of the road location, while others required the specific road-structure scene (such as straight road) as the first road image. These requirements on the road initializations are clumsy for the automatic road-detection task. For instance, in [10] they are very myopic since the curve propagates according to genetic operator, crossover operator, and mutation operator; that is, the children individual is selected under the influence of a very small neighborhood of image pixels. Therefore, the automatic initialization technique, which is able to extract the location of any type of the lane shapes, is important and necessary. If the application requires full automatic lane-markings extraction, global information about the structure of interest (e.g., shape) has to be encoded in the detection algorithm. However, most of the methods that rely only on global constraints do not reflect shape variations at small scales [12]. Approaches that combine both local and global types of information are usually a tradeoff between global shape alignment and fidelity to local image features.

In order to address these problems, different from the methods discussed before, we propose a new method to robustly detect the lane boundaries on a variety of different road types under a variety of illumination changes and shadowing by introducing an adaptive randomized Hough transform (HT), in which the markings are first globally and rather coarsely detected in a reduced image; this estimate can be then refined in the original image. The experimental results and comparison with other methods demonstrate the effectiveness and efficiency of the proposed method.

The principal contributions of this paper are as follows:

- presentation of the system architecture and the basic strategy of the Springrobot: a prototype autonomous vehicle;
- description of the adaptive randomized HT (RHT) for robust and accurate detection of lane markings without manual initialization or *a priori* information under different road environments.

The remainder of this paper is organized as follows. Section II presents the system architecture and implementation strategy of the Springrobot. In Section III, the model of lane boundary is briefly described. Section IV describes color-feature selection and image processing. We propose the adaptive RHT (ARHT) in Section V. In Section VI, experiments supporting the feasibility of recognizing various kinds of lane boundaries and showing

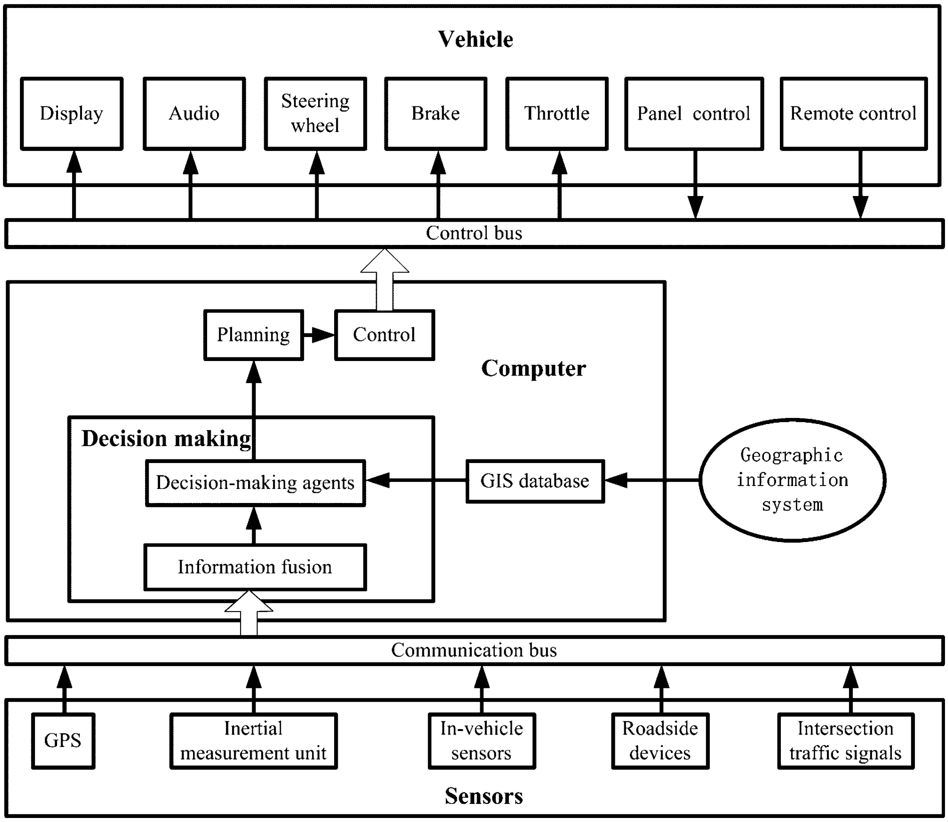


Fig. 2. System architecture of Springrobot.

the advantages of the ARHT algorithm are described. Finally, the conclusion and future work are presented in Section VII.

II. Springrobot: Prototype for Autonomous Vehicles

Springrobot, shown in Fig. 1, is an experimental autonomous vehicle that is equipped with computers; various sensors; and communicating, remove controlling, automatic braking, accelerating, and steering capabilities.

Its main target is the development of an active safety system that can also act as an automatic pilot for a land vehicle on structured highways, unstructured road, or unpaved road in rural or city areas. The ability to perceive the environment is essential for the intelligent vehicle. It has been proven that vision sensor is most effective after decades of research, so the perception system of the Springrobot is mainly based on machine vision, combining with other sensors, such as an infrared (IR) sensor, radar, lidar, laser, differential global position system (DGPS), accelerometer, gyroscope, etc.

A. System Architecture

Fig. 2 shows the three-layer system architecture. The sensory layer includes air-position indicators (APIs) and sensor-specific drivers for data collection and communication with different types of in-vehicle sensors and roadside devices. The computing layer contains a geographic information system (GIS) database, decision making, planning, and control, which is implemented by computers. The vehicle layer consists of warning devices, such as display; executing devices, such as an automatic steering wheel; and commanding devices, such as a panel.

B. Machine-Learning Approaches

Much of modern statistical and adaptive signal processing relies on learning algorithms of one form or another. Machine-learning approaches have been used to train computer-controlled vehicles to correctly steer around or detect an obstacle when driving on a variety of road types. For example, the system [14] has used its learned strategies to recognize vehicles, although some approaches to machine learning have been applied in robot navigation, a variety of new techniques that offer tremendous potential for autonomous vehicle applications, which still need further research and development to shorten the way to practical and reliable intelligent vehicle. Many machine-learning systems can be usefully characterized in terms of four generic modules including the performance system, critic, generalizer, and experiment generator [15]. Thus, the autonomous learning problem can be demonstrated in Fig. 3 and described as follows.

Task T: perceiving traffic conditions, making decisions, planning paths, and controlling the vehicle to run on structured highways and unpaved road in a rural or city area by vision sensors, IR sensors, radar, lidar, laser, DGPS, accelerometer, gyroscope, etc.

Performance measure P: average distance and velocity traveled under various road conditions before an error (as judged by a human overseer).

Train experience E: a set of information captured by various sensors and stored in GIS, as well as warning, steering, braking, or accelerating commands recorded while observing a human driver.

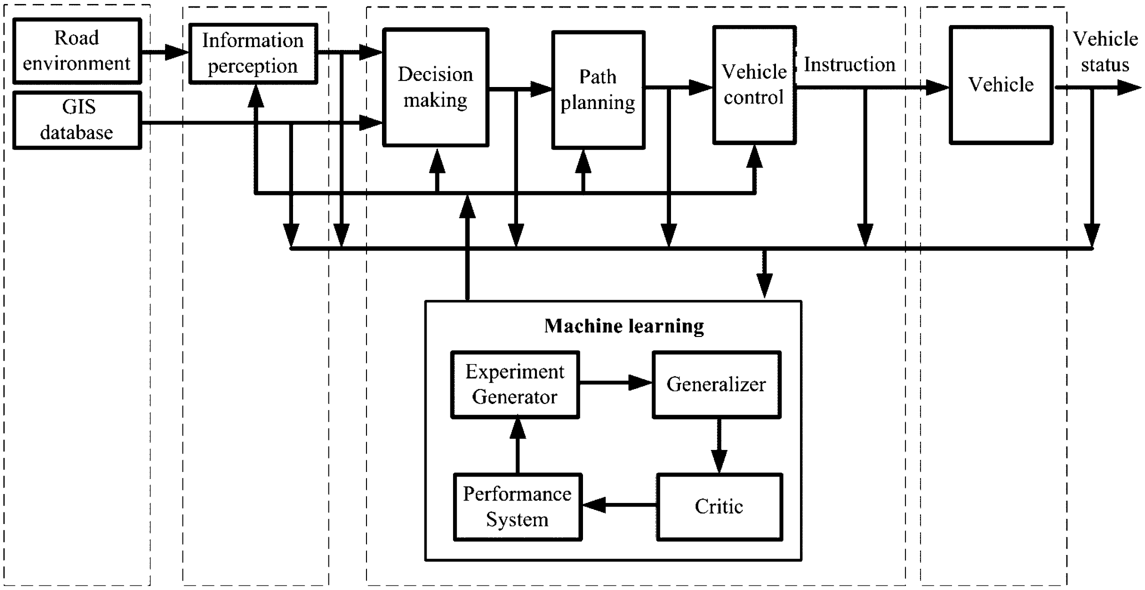


Fig. 3. Learning-based control strategy for Springrobot.

III. Model of Lane Boundaries

The lane-boundary model plays an important role in lane detection. Lane modeling has to make some assumptions about the road structure in the real world in order to fully recover 3-D information from the 2-D static image. In this paper, it is assumed that the two markings of the lane are parallel to the ground plane. According to [16] and [17], the markings and pavement boundaries can be approximated by circular arcs in a flat ground plane in the length of the visible road. Due to the use of the parallel knowledge of roads on the ground plane, adaptation and robustness to different road conditions, shadows, and noises is achieved. A circular arc with curvature k' is approximated by a parabola of the form

$$x = 0.5 \times k' \times y^2 + m \times y + b'. \quad (1)$$

Under the perspective projection, these circular arcs on the ground plane are transformed into curves in the image plane. These curves can be closely approximated in a single image by

$$u = k/(v - hz) + b \times (v - hz) + vp \quad (2)$$

where the parameter hz is the row in the image plane corresponding to the horizon of the ground plane and can be determined by the camera calibration. The parameter k is linearly proportional to the curvature of the arc on the ground plane. The parameter vp is a function of the tangential orientation of the arc on the ground plane, with the same coupling to the curvature as well (the amount of this coupling depends on the camera tilt). The parameter b is a function of the offset of the arc from the camera on the ground plane, with coupling to arc curvature and tangential orientation (again, the relative contributions of these couplings depends on the camera tilt). While the radius of the curvature and tangent orientation of the left and right lane edges will differ slightly, constraining the left and right lane edges to have the same k and vp parameters closely approximates the actual lane-edge shapes for all but very small radii of curvature. The problem of detecting lane boundaries is then formulated as estimating the parameters k, b, and vp for the left and the right lane boundaries in an image.

IV. Color-Feature Selection and Image Preprocessing

In general, lane-detection success or failure depends primarily on how distinguishable a marking is from its surroundings. If the marking is very distinctive, a simple detector can be used to detect it. If the marking has low contrast or is camouflaged, imposing a great deal of prior knowledge about a road scene will achieve the robust detection, but it lacks generality. The degree to which a detector can discriminate marking and background is directly related to the feature space used. In principle, a wide range of features could be used for detection, including color, texture, and shape. Each potential feature space typically has dozens of tunable parameters; therefore, the full set of potential features that could be used for detection is enormous. Because of the importance of color in lane markings, we only consider color features in this paper. The set of color candidate features are composed of linear combinations of red, green, blue (RGB) channel values. For our experiments, we have chosen the following set of feature-space candidates [18].

$$F \equiv \{w_1 R + w_2 G + w_3 B\}, \quad w_i \in \{-2, -1, 0, 1, 2\} \quad i = 1, 2, 3. \quad (3)$$

That is, linear combinations composed of integer coefficients between −2 and 2. All features are normalized into the range of 0–255. By experiments, we found that the form $w_1 = 1, w_2 = 1$, and $w_3 = 0$ is suitable for lane detection. This case is consistent with the fact that the red and green channels of colored road-scene image have good contrast properties for both white and yellow lane markings. However, the R channel is used in [19].

In order to obtain the edge information, the gradient values of the input image $f(u, v)$ are calculated using the 3×3 Sobel operator with very low threshold. Thus, two images can be obtained: a graylevel edge magnitude map $f_m(u, v)$, denoting gradient magnitude of the input image, and a grayscale edge direction map $f_g(u,v)$, denoting the ratio of vertical and horizontal gradient magnitude of the input image.

$$\begin{aligned} f_u(u,v) &= \{f(u+1,v-1)+2f(u+1,v)+f(u+1,v+1)\} \\ &\quad -\{f(u-1,v-1)+2f(u-1,v)+f(u-1,v+1)\}. \end{aligned} \tag{4}$$

$$\begin{aligned} f_v(u,v) &= \{f(u-1,v+1)+2f(u,v+1)+f(u+1,v+1)\} \\ &\quad -\{f(u-1,v-1)+2f(u,v-1)+f(u+1,v-1)\}. \end{aligned} \tag{5}$$

$$\begin{aligned} f_m(u,v) &= \sqrt{(f_u(u,v))^2+(f_v(u,v))^2} \approx |f_u(u,v)|+|f_v(u,v)|. \end{aligned} \tag{6}$$

$$f_g(u,v) = f_v(u,v)/f_u(u,v). \tag{7}$$

V. ARHT

The HT [20] is a popular method for extracting global curve segments from an image. It attracts a great amount of attention from the mainstream image-processing community and has been used for lane detection [12], [21]–[23]. Its independent use of image features makes it suitable for implementation in a parallel computing system. The HT was then generalized to nonanalytic shapes by Ballard [24]. This method is able to detect any arbitrary shape undergoing a geometric transformation in an image. However, increasing the number, range, or accuracy of the parameters of the geometric transformation may lead to high computation efforts, which are practically not amenable. In the context of straight-lines detection, Illingworth and Kittler [25] proposed to implement the HT efficiently by using an adaptive accumulator array and a coarse-to-fine strategy. Obvious advantages of this approach are that the process can go on until a given accuracy is reached without increasing the size of the array. A two-step adaptive generalized HT for the detection of nonanalytic objects undergoing weak affine transformations in images was introduced in [26].

The RHT offers a different approach to achieve increased efficiency in the detection of analytic curves [27], [28], whereby a set of n pixels is randomly selected from the edge image, determining the n parameters of the curve of interest. The advantages of the RHT include high parameter resolution, infinite scope of the parameter space, small storage requirements, and high speed. However, the entire process has to be repeated for every combination of the discrete parameter values. If wide range and high accuracy are required for the parameters, both computational time and storage space become very large.

Motivated by the above problems, here we present a new adaptive RHT for lane detection in the application of intelligent vehicles. This method has both advantages of adaptive HT and RHT.

Fig. 5, combining with Fig. 4, is a flowchart that illustrates the implementation strategy used to detect the markings in a highway scene. The scheme consists of presenting the image information by graylevel edges instead of binary level edges, reducing the size of the original image, so that the marking can be located coarsely and rapidly, and investigating the interesting area by the coarse location and relatively increasing the quantized accuracy. This cycle of events continues until parameters are determined to a reasonable accuracy. Located parameters can be used to identify, by an inverse mapping, the position and orientation of vehicle relative to lane.

A. Reduction of 3-D Parametric Space to the 2-D and the One-Dimensional (1-D) Space

The main bottlenecks of the HT-related techniques are their computational complexity and storage requirements. To simplify the complexity of algorithm, the 3-D parametric space should be reduced to two dimensions. It is possible to eliminate the feature-specific b parameter by making use of local feature-orientation information [16], [17]. Taking the derivative of the curve (2), solving for b, and substituting it into the feature equation, we can obtain the relationship among a point on any road feature, the local feature, the local feature tangent, and the k and vp parameters shared by all the road features

$$du/dv = -k/(v-hz)^2 + b. \tag{8}$$

$$u = 2k/(v-hz) + (du/dv)(v-hz) + vp. \tag{9}$$

Using (9) rather than (8) to estimate the parameter k and vp is because one or more lane markings and other objects in the image, such as shoulders and lane fences, have edges sharing the same lane structure. Among the three lane structure parameters, these edges approximately share the two parameters k and vp. The difference between them is the value of the parameter b. This property allows us to estimate k and vp robustly and quickly by RHT, just as detecting a circle, ellipse, or parabola by RHT. Thus, k and vp can be estimated directly from the raw edge-point location and orientation data without the need to group the edge points together into individual features. From (9), road boundaries can be detected by using only a 2-D accumulator array. Edge gradient information is used to estimate the du/dv term.

$$du/dv = -f_g(u,v). \tag{10}$$

The adaptive RHT can be used to estimate k and vp, associated with b. A pair of pixels (u_1,v_1) and (u_2,v_2) are sampled in the gray-edge map, then k and vp can be calculated as

$$k = \frac{(u_1-u_2)+f_g(u_1,v_1)(v_1-hz)-f_g(u_2,v_2)(v_2-hz)}{2(1/(v_1-hz)-1/(v_2-hz))}. \tag{11}$$

$$vp = u_1 - 2k/(v_1-hz) + f_g(u_1,v_1)(v_1-hz). \tag{12}$$

Additionally, gradient direction represents a lot of information on the contour. The use of the gradient directional information acts favorably in two points [29]: It increases the detection speed and improves parameter accuracy by reducing the wrong evidences. We reduce inefficient accumulation using directional information. For the two points that are obviously not on the lane boundaries, due to a random sample, they are likely to be picked up in RHT. We have to calculate parameter cell

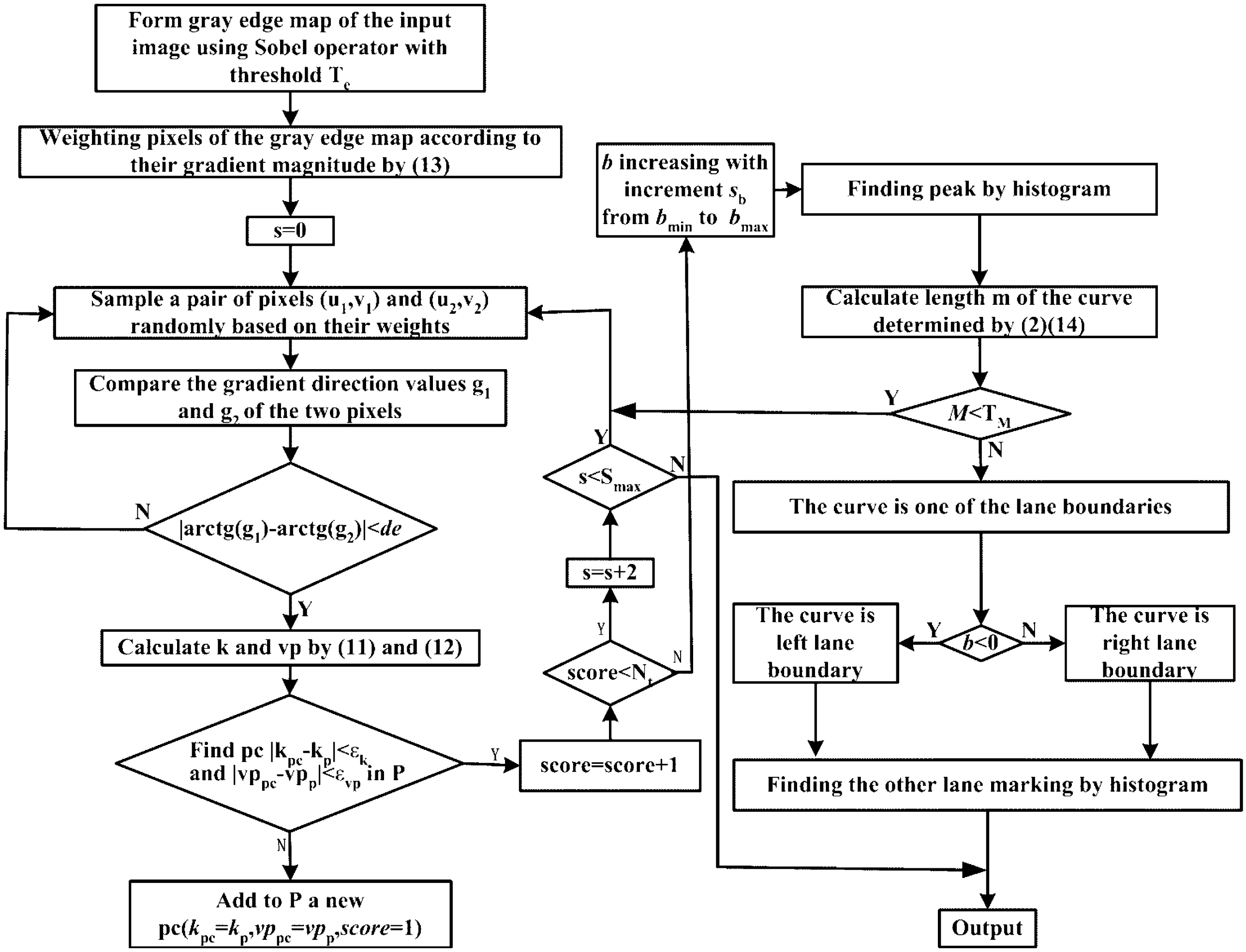

Form gray edge map of the input image using Sobel operator with threshold T_c
Weighting pixels of the gray edge map according to their gradient magnitude by (13)
s=0
Sample a pair of pixels (u_1,v_1) and (u_2,v_2) randomly based on their weights
Compare the gradient direction values g_1 and g_2 of the two pixels
N
$|arctg(g_1)-arctg(g_2)|<de$
Y
Calculate k and vp by (11) and (12)
Find pc $|k_{pc}-k_p|<\varepsilon_k$ and $|vp_{pc}-vp_p|<\varepsilon_{vp}$ in P
Y
N
Add to P a new $pc(k_{pc}=k_p, vp_{pc}=vp_p, score=1)$
score=score+1
$score<N_t$
Y
N
s=s+2
$s<S_{max}$
Y
N
b increasing with increment s_b from b_{min} to b_{max}
Finding peak by histogram
Calculate length m of the curve determined by (2)(14)
$M<T_M$
Y
N
The curve is one of the lane boundaries
The curve is left lane boundary
Y
$b<0$
N
The curve is right lane boundary
Finding the other lane marking by histogram
Output

Fig. 4. Processing procedure of the ARHT.

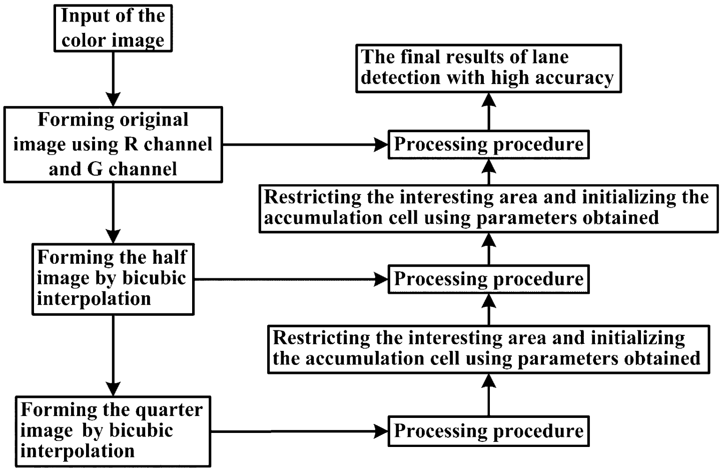

Input of the color image
Forming original image using R channel and G channel
Forming the half image by bicubic interpolation
Forming the quarter image by bicubic interpolation
Processing procedure
Restricting the interesting area and initializing the accumulation cell using parameters obtained
Processing procedure
Restricting the interesting area and initializing the accumulation cell using parameters obtained
Processing procedure
The final results of lane detection with high accuracy

Fig. 5. Flow chart of adaptive RHT.

$\mathbf{p}$ of a curve that passes the two points and searches the parameter cell set $\mathbf{P}$. If there is no $\mathbf{p}$ in $\mathbf{P}$, a new parameter cell will inserted into $\mathbf{P}$; thus, the list structure will increase. If gradient-direction information can be utilized, the result that two points are not lane boundaries would be detected and further work would not be done. Given a threshold de for two points d_1 and d_2 that is sampled randomly, the gradient directions g_1 and g_2 at the two points are judged whether they satisfy the condition $|\mathrm{arc}tg(g_1) - \mathrm{arc}tg(g_2)| \leq de$. If not, the two points are not thought to be on the lane boundaries and resampling will be done.

B. Using Graylevel Edge Maps Instead of Binary-Level Edge Maps

The task of curve detection can be conducted on a binary-edge image that may be obtained from graylevel images by either simple thresholding operations or by some standard edge-detection techniques. Suppose that the curves to be detected can be expressed by a parametric function $f(\mathbf{a}, \mathbf{d}) = 0$, with $a = [\alpha_1, \ldots, \alpha_n]^t$ containing n independent parameters and $\mathbf{d} = \mathbf{d}(x, y)$ being the coordinates of a "white" pixel.

However, when using gradient operator to obtain edges, it is difficult to determine an optimal threshold value for selecting only true road lanes corresponding to the painted yellow and white lane mark or road boundaries among many noisy edges. Also, in many road scenes it is not possible to select a suitable threshold that eliminates noise edges without eliminating many of the lane-edge points of interest. In scene analysis or 3-D reconstruction, curves often disappear during the edge-detection processes, which becomes critical for the succeeding processes. Therefore, a better alternative is to use whole gray-edge map and no useful information is lost. However, the computational cost is high if all pixels are included; a very low threshold value is assumed to insure the existence of true edges corresponding to road boundaries and the remaining problem is the selection of the real boundaries among many candidate edges. For the gray-edge magnitude map mentioned before, a very low threshold T_e (e.g., 0.1 or 0.2) is set to remove those points that do not belong to lane markings absolutely.

In RHT based on a binary edge map, every edge pixel is sampled uniformly, without considering its probability of being on a certain curve. In the ARHT, inspired by particle filtering [30], pixels in gray-edge map is weighted according to its gradient magnitude, then the pixels are sampled according to their weight, i.e., pixels with larger gradient magnitudes are sampled more frequently. In this paper, the weight of a pixel $p(u, v)$ is defined as

$$w^{(n)}(u, v) = f_m^{(n)}(u, v) \Bigg/ \sum_{u=1}^{W} \sum_{v=1}^{H} f_m^{(n)}(u, v) \tag{13}$$

where

$$\sum_{n=1}^{N} w^{(n)} = 1.$$

The array (u, v) is the position of the pixel $p, f_m(u, v)$ is the gradient magnitude of $p(u, v), W$ and H is the width and the height of the grayscale edge map, respectively, and $N = W \times H$. The pixels are sampled as follows.

Step 1) Form a sample-set D using pixels whose gradient magnitude is nonzero.

Step 2) Calculate the weight of $p(u, v)$, as defined in (13).

Step 3) Store together with cumulative probability as $(\mathrm{d}^{(\mathrm{n})}, w^{(n)}, c^{(n)})$, where $C^{(0)} = 0, C^{(n)} = C^{(n-1)} + w^{(n)}(n = 1, \ldots, N)$.

Step 4) Generate a random number $r \in [0, 1]$.

Step 5) Find, by binary subdivision, the smallest q for which $C^{(q)} \geq r$.

We select the q element of D to be the sampled pixel. Following the process that the parameters k and vp are estimated, the correctness of the parameters k and vp should be verified. Not as straight line, two parameters can determine a line, the curve defined in (2) cannot be determined only by parameters k and vp. To verifying the curve, another parameter b has to be included. The parameter b of the model can be found by histogramming the accumulation of gradient magnitude of points on the curve supposed true in the graylevel edge image. The pixels through the curve can be accumulated as

$$M = \sum f_m(u_c, v_c) \tag{14}$$

where M represents the length of the curve determined by k, vp and $b, (u_c, v_c)$ is a pixel on the assumed curve and $f_m(u_c, v_c)$ is the gradient magnitude of (u_c, v_c). If M exceeds a specified threshold, the curve is true.

After a marking is detected, the other marking can be obtained by some post analysis, such as a simple histogram step.

C. Determining Parameters Coarsely and Increasing Quantized Accuracy Relatively by the Multiresolution Strategy

A multiresolution strategy to achieve an accurate solution rapidly and to decrease the running time to meet the real-time requirement was employed at the stage. The size of the original image is reduced to $1/2^z$, where $\mathrm{z} = 1, 2$, by bicubic interpolation. The reduced images are called as quarter image and half image, respectively. In these images with lower resolution, we can roughly and efficiently locate the global optima without regarding the accuracy using the ARHT with fixed quantized accuracy. The parameters resulting from the previous step can be used as starting values of another ARHT for more accurate location of vehicle. The parameter search can, therefore, be restricted to a small area around the previous solution, saving time and storage complexities. First, the model of marking with k_q, vp_q and b_q is detected in the quarter image. In the second stage, a smaller search area and a finer step size are used to obtain the better model of marking with k_h, vp_h and b_h in the half image. At last, a smaller search area and a finer step size are used to obtain the final model of marking with k, vp and b in the original image. This coarse-to-fine location offers us an acceptable solution at an affordable computational cost and, thus, speeds up the process of lane detection.

When the quarter image is restored into the half image and the half image is restored into the original image, the relationships among the parameters of marking model are depicted as

$$\begin{aligned} k_h = 4k_q, vp_h = 2vp_q, b_h = b_q \\ k = 4k_h, vp = 2vp_h, b = b_h. \end{aligned} \tag{15}$$

Now, let us discuss the error criterion for regarding two elements being the same in ARHT. When $\mathbf{P}$ is the usual accumulation array, two elements are regarded as the same as they are discretized into the same coordinates. One alternative is that two elements are regarded as the same if we have $\mathrm{dis}(\mathbf{a}, \mathbf{param}(p) < \varepsilon)$ under a given distance measure $\mathrm{dis}(\mathbf{x}, \mathbf{y})$ and a tolerance ε. The tolerance ε is more small, the accuracy is more high in the process of using ARHT to analyze image. The tolerance ε would be set smaller and smaller for the accurate model of marking. Although the ε is fixed in this paper, in fact the accuracy is improved because of the increasing of k, vp with the restoring of reduced image. Fig. 6 shows the multiresolution approach for lane detection.

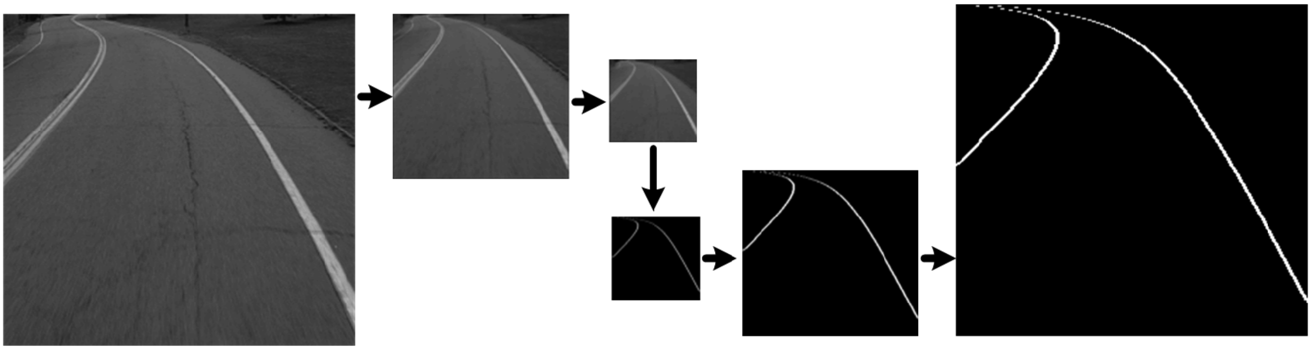


Fig. 6. Multiresolution algorithm for detecting the lane rapidly and accurately.

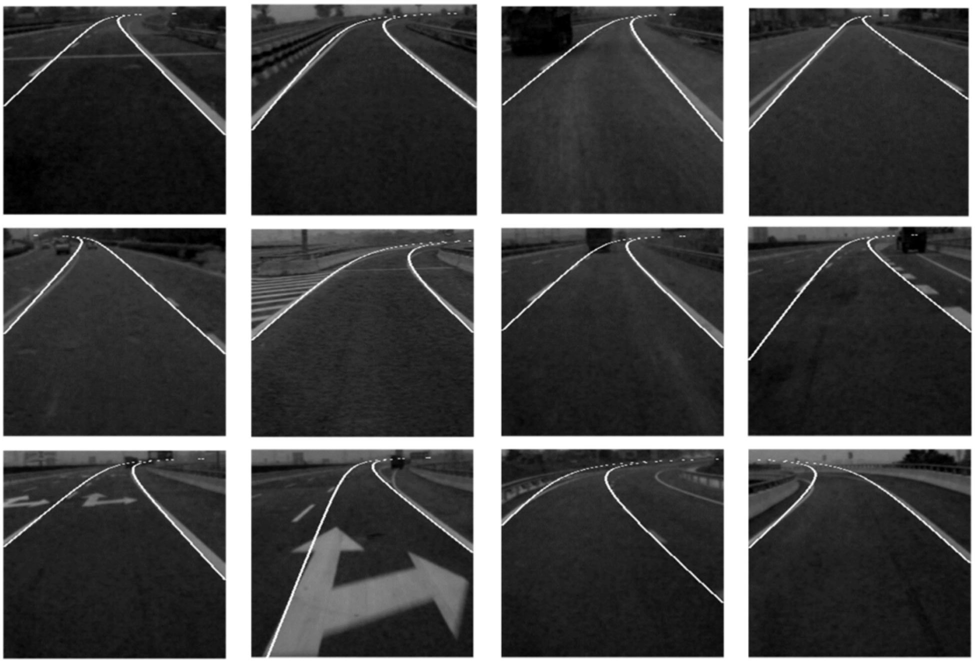


Fig. 7. Experimental results of different road scenes.

VI. Experiments

This section presents the performance of the proposed method in the real road scenes. We can extract the left and right lane boundaries. The algorithm is tested on some images from video grabbed by an onboard camera in our laboratory and images provided by Robotics Institute, Carnegie Mellon University (CMU), Pittsburgh, PA. All experimental images are 24-bit color images of size 256 × 240. Fig. 7 shows some of our experimental results of lane-boundary detection, where detected boundaries are superimposed onto the original images. These images represent various real highways scenes, including a lane whose left and right markings are solid, a lane whose left marking is solid and right marking is broken, a lane whose left marking is broken and right marking is solid, a lane whose left and right markings are broken, a lane with shadows, a lane with highlight in far field, a lane whose left marking has big blank, and also a lane whose markings are fragmentary. The experiments show that the method retains the desirable HT characteristics of robustness to extraneous data and the ability to detect model parameters from disturbed data, although imperfect detection occasionally happens because of traffic signs drawn on the road.

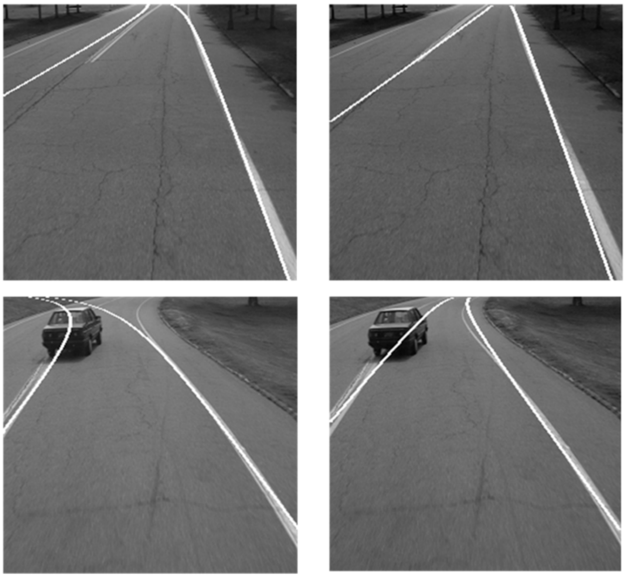


Fig. 8. Comparison of the genetic algorithm and ARHT for lane detection.

Fig. 8 demonstrates the performance of genetic-algorithm-based lane detection [10] and ARHT-based lane detection. The experimental comparison seems to indicate that the latter has some advantages over the former.

VII. Conclusion

In this paper, we demonstrate the prototype and detail tasks of lane detection. The accuracy and robustness of the road-boundary detection for an intelligent vehicle is a formidable task under a variety of road pavement types, lane structures, weather conditions, and noises. An adaptive RHT, an efficient way of implementing the RHT, is employed to deal with these difficulties and, at the same time, preserving its advantage of high accuracy, especially for noisy images. To reduce the high computational cost associated with the original input image, the size of the input image is reduced. To deal with a cluttered scene and to detect the true lane edges, a gray-edge map with a very small threshold value is used. To simplify the problem, the 3-D Hough space is reduced to two dimensions. To save memory storage and decrease computational cost, randomized sampling and an iterative "coarse-to-fine" accumulation and search strategy are adopted.

Future work is to further reduce the running time in the lane detection and to detect and recognize vehicles based on machine learning.

References

[1] A. Broggi, P. Cerri, and P. C. Antonello, "Multi-resolution vehicle detection using artificial vision," in *Proc. Intelligent Vehicle Symp.*, 2004, pp. 310–314.

[2] R. Bishop. (2003) *A Survey of Intelligent Vehicle Applications Worldwide: Overview* [Online]. Available: www.IVsource.net

[3] N. Zheng, S. Tang, H. Cheng, Q. Li, G. Lai, and F. Wang, "Toward intelligent driver-assistance and safety warning systems," *IEEE Intell. Syst.*, vol. 19, pp. 8–11, Mar./Apr. 2004.

[4] E. D. Dickmanns, "The development of machine vision for road vehicles in the last decade," in *Proc. Intelligent Vehicle Symp.*, vol. 1, 2001, pp. 268–281.

[5] V. Kastrinaki, M. Zervakis, and K. Kalaitzakis, "A survey of video processing techniques for traffic applications.," *Image Vision Comput.*, vol. 21, pp. 359–381, 2003.

[6] M. Bertozzi, A. Broggi, and M. Cellario, "Artificial vision in road vehicles," *Proc. IEEE*, vol. 90, pp. 1258–1271, July 2002.

[7] Y. Wang, E. K. Teoh, and D. Shen, "Lane detection and tracking using B-snake," *Image Vision Comput.*, vol. 22, pp. 269–280, 2004.

[8] Y. U. Yim and S. Y. Oh, "Three-feature based automatic lane detection algorithm (TFALDA) for autonomous driving," *IEEE Trans. Intell. Transport. Syst.*, vol. 4, pp. 219–225, Dec. 2003.

[9] J. C. McCall and M. M. Trivedi, "An integrated, robust approach to lane marking detection and lane tracking," in *Proc. IEEE Intelligent Vehicles Symp.*, 2004, pp. 533–537.

[10] T. Liu, N. Zheng, H. Cheng, and Z. Xing, "A novel approach of road recognition based in deformable template and genetic algorithm," in *Proc. Intelligent Transportation System Conf.*, vol. 2, 2003, pp. 1251–1256.

[11] D. J. Kang and M. H. Jung, "Road lane segmentation using dynamic programming for active safety vehicles," *Pattern Recogn. Lett.*, vol. 24, pp. 3177–3185, 2003.

[12] J. McDonald, "Detecting and tracking road markings using the Hough transform," in *Proc. Irish Machine Vision and Image Processing Conf.*, 2001, pp. 1–9.

[13] J. W. Park, J. W. Lee, and K. Y. Jhang, "A lane-curve detection based on an LCF," *Pattern Recogn. Lett.*, vol. 24, pp. 2301–2313, 2003.

[14] T. Kato, Y. Ninomiya, and I. Masaki, "Preceding vehicle recognition based on learning from sample images," *IEEE Trans. Intell. Transport. Syst.*, vol. 3, pp. 252–260, Dec. 2002.

[15] T. M. Mitchell, *Machine Learning*. Beijing, China: China Machine, 2003, pp. 12–13.

[16] K. Kluge, "Extracting road curvature and orientation from image edge points without perceptual grouping into features," in *Proc. Intelligent Vehicle Symp.*, 1994, pp. 109–114.

[17] K. Kluge and S. Lakshmanan, "Lane boundary detection using deformable templates: Effects of image sub-sampling on detected lane edges," in *Proc. 2nd Asian Conf. Computer Vision*, 1995, pp. 329–339.

[18] R. T. Collins and Y. Liu, "On-line selection of discriminative tracking features," in *Proc. 9th IEEE Int. Conf. Computer Vision*, vol. 2, 2003, pp. 346–352.

[19] B. Southall and C. J. Taylor, "Stochastic road shape estimation," in *Proc. 8th IEEE Int. Conf. Computer Vision*, 2001, pp. 205–212.

[20] P. V. C. Hough, "Method and Means for Recognizing Complex Patterns," U.S. Patent 3 069 654, 1962.

[21] K. Hashimoto, S. Nakayama, and T. Saito, "An image-processing architecture and a motion control method for an autonomous vehicle," in *Proc. IEEE Symp. Intelligent Vehicles*, 1992, pp. 120–125.

[22] B. Yu and A. K. Jain, "Lane boundary detection using a multiresolution Hough transform," in *Proc. Int. Conf. Image Processing*, 1997, pp. 784–751.

[23] B. Fardi and G. Wanielik, "Hough transformation based approach for road border detection in infrared image," in *Proc. Intelligent Vehicle Symp.*, 2004, pp. 549–554.

[24] D. H. Ballard, "Generalizing the Hough transform to detect arbitrary shapes," *Pattern Recogn.*, vol. 13, no. 2, pp. 111–122, 1981.

[25] J. Illingworth and J. Kittler, "The adaptive Hough transform," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. PAMI-9, pp. 690–698, Sept. 1987.

[26] O. Ecabert and J. P. Thiran, "Adaptive Hough transform for the detection of natural shapes under weak affine transformations," *Pattern Recogn. Lett.*, vol. 25, pp. 1411–1419, 2004.

[27] L. Xu and E. Oja, "Randomized Hough transform (RHT): Basic mechanisms, algorithms, and computational complexities," *CVGIP: Image Understanding*, vol. 57, no. 2, pp. 131–154, 1993.

[28] Z. Cheng and Y. Liu, "Efficient technique for ellipse detection using restricted randomized hough transform," in *Proc. Inform. Technol.*, vol. 2, 2004, pp. 714–718.

[29] E. Montiel, A. A. Aguado, and M. S. Nixon, "Improving the Hough transform gathering process for affine transformations," *Pattern Recogn. Lett.*, vol. 22, pp. 959–969, 2001.

[30] S. Arulampalam, S. Maskell, and N. Gordon, "A tutorial on particle filters for on-line nonlinear/non-Gaussian Bayesian tracking," *IEEE Trans. Signal Processing*, vol. 50, pp. 174–188, Feb. 2002.

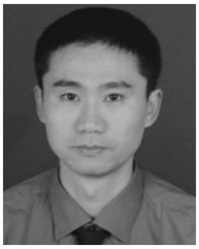
Qing Li received the B.S. degree in aviation weaponary engineering from the Air Force Engineering University, Xi'an, China, in 1993. He is working toward the Ph.D. degree at the Institute of Artificial Intelligence and Robotics, Xi'an Jiaotong University, Xi'an, China.

His research interests include computer vision and pattern recognition.

Nanning Zheng (SM'93) graduated from the Department of Electrical Engineering, Xi'an Jiaotong University, Xi'an, China, in 1975 and received the M.E. degree in information and control engineering from Xi'an Jiaotong University in 1981 and the Ph.D. degree in electrical engineering from Keio University, Tokyo, Japan, in 1985.

He is a Professor and the Director of the Institute of Artificial Intelligence and Robotics, Xi'an Jiaotong University. He serves as Executive Editor of *Chinese Science Bulletin*. His research interests include computer vision, pattern recognition, computational intelligence, image processing, and hardware implementation of intelligent systems.

Dr. Zheng became a Member of the Chinese Academy Engineering in 1999. He served as General Chair of the International Symposium on Information Theory and Its Applications and General Co-Chair of the International Symposium on Nonlinear Theory and Its Applications, both in 2002. He also is a Member of the first Board of Governors of the IEEE ITS Society. He has been the Chinese Representative on the Governing Board of the International Association for Pattern Recognition since 2000.



Hong Cheng received the Ph.D. degree from Xi'an Jiaotong University, Xi'an, China, in 2003.

Since 2000, he has been a Teaching Assistant with the Automation Department, Xi'an Jiaotong University. He currently is a Lecturer at the Institute of Artificial Intelligence and Robotics, Xi'an Jiaotong University. His research interests include simultaneous localization and map building, machine vision, mobile robotics, unmanned vehicles, and intelligent systems.