Computer Vision Technology for Vehicular Robot to Follow Guided Track Using Neuro-Fuzzy System

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Abstract. This paper describes computer vision technology for a camera-based automatic guided vehicular mobile robot using neuro-fuzzy control system to follow guide lanes with a camera. Without a complicated geometric computing from a camera image to robot-position-localization in conventional researches, the proposed control system transfers the inputs of image sensor into the output of steering values directly. The neuro-fuzzy controller replaces the human driving skill of nonlinear relation between vanishing lines of guide lanes on the camera image and the steering angle of vehicular robot. In straight and curved road, the driving performances by the proposed control scheme are measured in simulation and experimental test.

Keywords: Computer vision · Neuro-fuzzy control · Vehicular robot

1 Introduction

In recent years, systems that integrate both visual sensors and an autonomous robot together have received a lot of attention, especially in the field of intelligent control [1–3]. Such systems can solve many problems that limit applications in previous robots. An important component of intelligent autonomous robot is to follow the road lane by lateral steering control of the robot. Vision system plays an important role in road following because it has the flexibility and the two-dimensional view. Also, many researchers have discussed possibilities for the application of intelligent control in autonomous robotic systems [4–7].

Several prototype systems of automated vehicles have been developed [3–8]. The lane-following vision control system architecture had developed in Carnegie-Mellon University is a general sample for autonomous vehicle [9, 10]. In the system, the vision system acquires a camera image and uses a typical image processing algorithm to extract road lane segments from the image. These road lane segments are transformed from the image coordinate system to the vehicle coordinate system, and used to the geometric reasoning module. This system has difficulties of heavy computation in given time because the geometric reasoning requires calculation of camera parameters and the lateral control depends on the parameters of road and the vehicular robot. In practical system, a sophisticated processing system might be able to solve these

F. Huang and A. Sugimoto (Eds.): PSIVT 2015 Workshops, LNCS 9555, pp. 167–178, 2016.
DOI: 10.1007/978-3-319-30285-0_14

difficulties. However the challenge of autonomous robot is that there is a limited time for the processing.

Pomerleau proposed ALVNN to overcome the difficulties [11]. The architecture of ALVNN(Autonomous Land Vehicle In a Neural Network) consists of a single hidden layer, feedforward network. The network receives a camera image of the road ahead, and produces the steering command that will keep the vehicle on the road lane. Input layer of the network has 960(32 × 30) units, which many input units require many calculation. To complete the calculation in given time, expensive computer system should be used.

In this paper, a computer vision technology using neuro-fuzzy control system for a camera-based automatic guided robot is presented, which uses a camera image to guide itself along guided lane. The proposed technology of the control system transfers the inputs of camera information into the output of steering angle directly, without a complex geometric reasoning from a visual image to a robot-centered representation in previous studies. The neuro-fuzzy controller replaces the human driving skill of non-linear relation between vanishing lines of road lanes on the camera image and the steering angle of the robot.

2 Vision-Based Control

As shown in Fig. 1, the geometrical reasoning between the robot's position and the guided lane can be described on the images using the following parameters:

(1) The lateral deviation of the vanishing point (*VD*) describes the lateral position of the current vanishing point (*VP*) for the reference vanishing point (VP_{ref}) as shown in Fig. 1(c) and (d). The parameter, *VD* depends upon the orientation of the robot on the road as shown in Fig. 1(a).
(2) The slopes of the vanishing lines (VL_l, VL_r) are defined by the tangent of the angle between the current vanishing line and the horizontal line as shown in Fig. 1(c). The slope is relative to the lateral position of the robot defined by the lateral distance between the center of the robot and the center of the guide lane.

The camera image contains the vanishing point and the vanishing lines of the guide lane. With these features on the image, the position and orientation of the robot between the guided lanes can be uniquely determined by geometric reasoning. On the basis of the above method, the vision-based-control method is introduced as follows:

Figure 1(c) is the current camera image, and Fig. 1(d) is the desired camera image obtained when the robot reaches the desired relative position and orientation on the guide lanes. The vision-based control system computes the error signals in terms of the lateral position and the slope derived from the vanishing point and vanishing line respectively on the image.

A steering angle generated by the proposed system makes that the vanishing point and the vanishing line on the current image coincide with the desired image. The lateral position of the vanishing point and the slope of the vanishing line computed from the linear vanishing line represent the relative position and orientation of the robot on the road. Then the robot is required to move its center to the lateral center of the guide lane

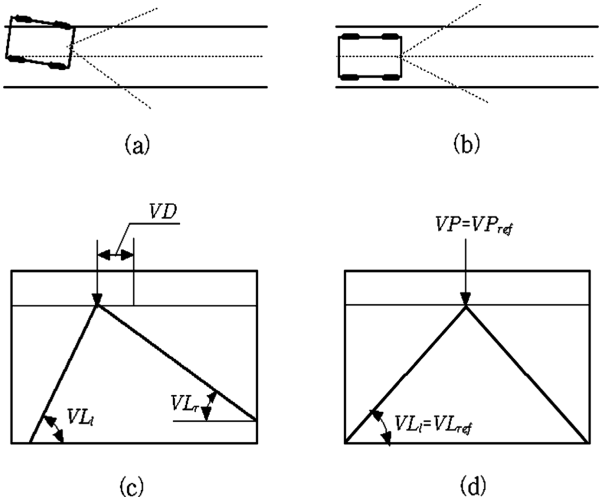

Fig. 1. Parameters of the guided lanes on the camera image which depends on the relation between the robot's orientation and position on guided lanes

and to parallel the guide lane by controlling its steering angle. It is significant that the vanishing point moves to the desired point in accordance with human's skill of driving.

3 Neuro-Fuzzy System

3.1 Neuro-Fuzzy System

The relation between the steering angle and the vanishing point and vanishing line on the camera image is a highly nonlinear function. A fuzzy and neural network is used for the nonlinear relation because it has the learning capability to map a set of input patterns to a set of output patterns. The inputs of the neuro-fuzzy system are the lateral position of the vanishing point and the slope of the vanishing line. The output of the neuro-fuzzy system is the steering angle value. Learning data could be obtained from human skill. After the neuro-fuzzy system learns the relation between input patterns and output patterns sufficiently, it makes a model of the relation between the position and the orientation of the robot, and that of the guide lane. Thus, a good model of the control task is obtained by learning, without inputting any knowledge about the specific robot's position and the guide lanes.

Generally, fuzzy control has a distinguished feature of being able to incorporate expert's control rules using linguistic descriptions of the rules. However, most experts often learn the control rules through trials and errors without clear linguistic expressions and they sometimes learn rules unconsciously. The identification of the control rules from the expert's experience is time consuming. Furthermore, tuning of the membership functions of the fuzzy controller needs "experts of the fuzzy controller".

Thus, neuro-fuzzy can automatically identify the expert's control rules and tune the membership functions from the expert's control data.

3.2 Configuration

Figure 2 shows a configuration of the proposed fuzzy controller using a neural network. The fuzzy model is of a linear hybrid model.

$$\begin{aligned} R^i &: \text{if } x_1 \text{ is } A_1^i, \text{ and} \ldots x_j \text{ is } A_j^i, \text{ and} \ldots, x_n \text{ is } A_n^i \\ &\text{then} \quad y^i = a_0^i + a_1^i x_1 + \ldots + a_n^i x_n \end{aligned} \tag{1}$$

$$w^i = \prod_{j=1}^{xn} A_j^i(x_j) \tag{2}$$

$$y^o = \frac{\sum_{i=1}^{n} w^i y^i}{\sum_{i=1}^{n} w^i} \tag{3}$$

where R^i is the i-th fuzzy rule, x_j is the j-th input variable, A_j^i is the i-th fuzzy variable for the j-th input variable, n is the number of rules, y^i is the i-th inferred output value, a_j^i is the coefficient, w^i is the true value in the premise and y^o is the inferred output value.

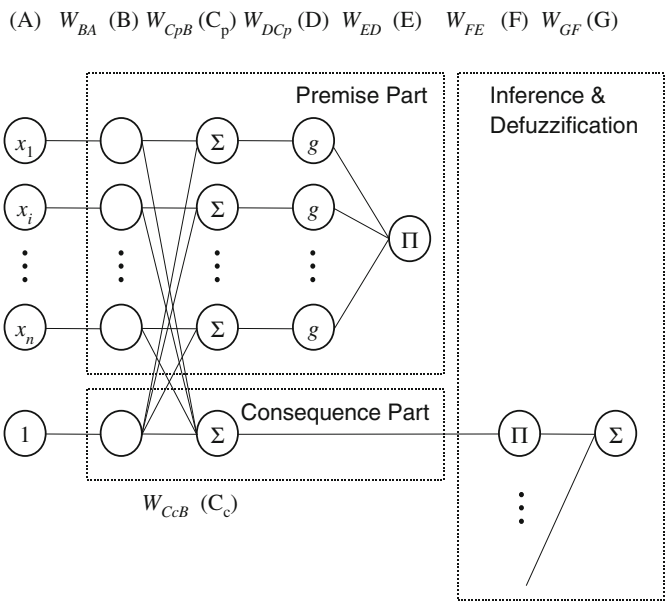

Fig. 2. Composition of neuro-fuzzy for a rule unit.

3.3 Premise

The network consists of seven layers and uses the back propagation algorithm for learning of the network as shown in Fig. 2. The figure shows the case where the controller has n-inputs(x_1, x_2, …, x_n) layer (A layer), one-output layer (G layer), and hidden layer for an unit rule. The outputs of the units with symbols $\sum$ denote sums of their inputs and $\prod$ denote products of their inputs.

The inputs into (A)-layer x_j are normalized by the connection weights W_{BA}. Normalized input variables, $\widehat{x}_j$ are given by

$$\widehat{x}_j = \frac{x_j}{Max|x_j|} = W_{BA}x_j \tag{4}$$

The sigmoid function $f(\widehat{x})$ are given by

$$f(\widehat{x}) = \frac{1}{1 + \exp\left(-W_{DCp}\left(\widehat{x} + W_{CpB}\right)\right)} \tag{5}$$

where W_{CpB} and W_{DCp} are to be modified through learning.

The output of the unit in (D)-layer $f(\widehat{x})$ is derived by removing the magnitude of the differentiated value of the sigmoid function $f(\widehat{x})$. The output of (D)-layer $f(\widehat{x})$ is the bell-shaped membership function that has a center of W_{CpB} and slope of W_{DCp}.

$$g(\widehat{x}) = \frac{1}{1 + \exp(-W_{DCs}(\widehat{x} + W_{CsB}))}\left(1 - \frac{1}{1 + \exp(-W_{DCs}(\widehat{x} + W_{CsB}))}\right) \tag{6}$$

3.4 Consequence

The consequences are expressed by linear equations. As shown in Fig. 2, the neurons of (B)-layer are connected with the neuron of (C_c)-layer through weight W_{CcB}, which expresses coefficient a_j^i of the linear equations. Therefore, the output of (C_c)-layer is expressed as follow:

$$y^i = a_0^i + a_j^i\widehat{x}_1 + \ldots + a_n^i\widehat{x}_n \tag{7}$$

The inferred value of the neuro-fuzzy is obtained from the product of the true values in the premises and the linear equations in the consequences.

$$y^{i\ddagger} = \frac{w^i y^i}{\sum_{n=1}^{n} w^i} \tag{8}$$

The output of (G)-layer can be expressed as follow:

$$y^{i\ddagger} = \sum_{i=1}^{n} y^{i\ddagger} \tag{9}$$

4 Computer Simulation

To simulate in computer as shown in Fig. 3, robot dynamic model, transformation of coordinate system, and control algorithms should be determined. The robot dynamic model uses the general model, and has specific parameters. Through transformation of coordinate system, the road could be displayed on the camera image plane visually.

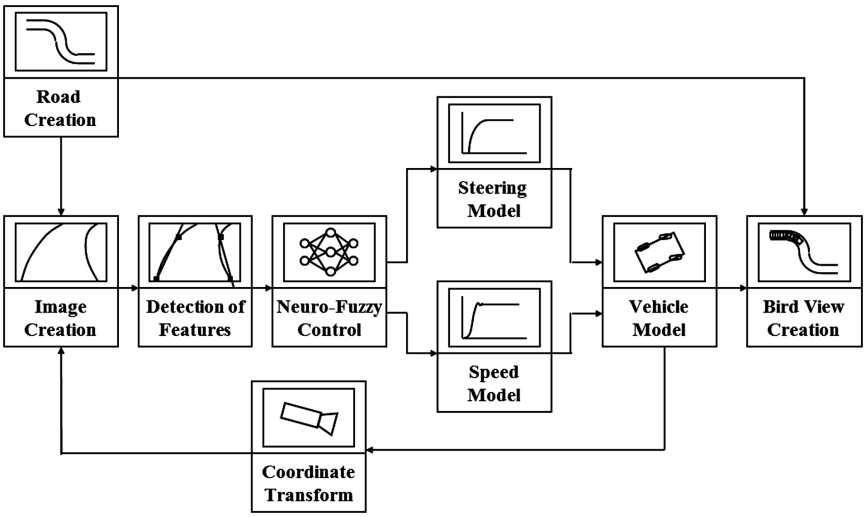

Fig. 3. Block diagram of computer simulation.

4.1 Robot Model

The general kinematic model of the vehicular robot with 4 wheels in world coordinates is shown in Fig. 4. The reference point (x_c^W, y_c^W) is located at the center point between the rear wheels. The heading angle θ for X^W-axis of the world coordinate system and the steering angle δ are defined in robot coordinate system.

Since robot coordinate system is used in control of autonomous robots, the current position (x_c^W, y_c^W) of the robot in world coordinate system is redefined as the point of origin for robot coordinate system. When the robot which has the distance L_v between front wheel and rear wheel runs with velocity v, the new position of the robot is

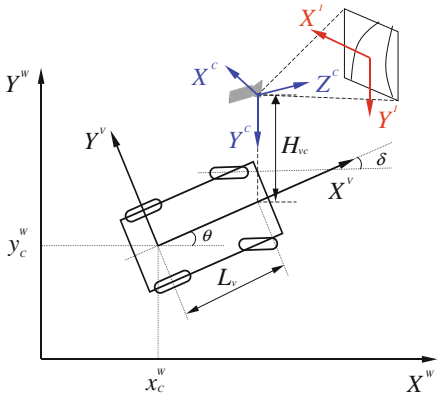

Fig. 4. Robot model and camera coordinate transformation model.

nonlinearly relative to steering angle δ of front wheel and heading angle θ determined by robot direction and road direction.

4.2 Transformation from Ground to Camera Image

In order to simulate in computer visually, the road has to be displayed on the camera image plane. Thus the coordinate transformations along the following steps are needed to determine the road of visual data from the road on the world coordinate system:

(1) Transformation from the world coordinate system to the robot coordinate system. The position (x_c^W, y_c^W) on the world coordinates is redefined as the origin for the robot coordinates.
(2) Transformation from the robot coordinate system to the camera coordinate system.
(3) Transformation from the camera coordinate system to the image coordinate system.

4.3 Simulation Results

Simulation results for the autonomous robot are shown in this section. The simulation program is developed from programming of robot's kinematics, transformation of coordinate system, and control algorithms by C++ in computer.

The performance of the proposed visual control system by neuro-fuzzy was evaluated using a robot driving on the track with a straight and curved shape as shown in Fig. 5. Figure 5 shows the bird's eye view of road map and the trajectories of robot's travel.

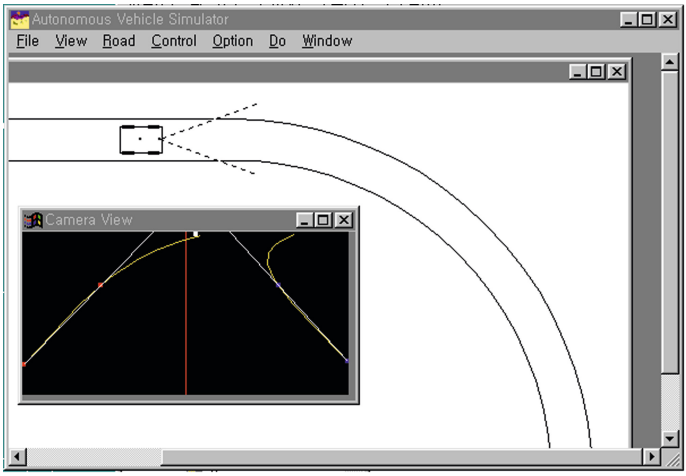

Fig. 5. Computer simulation of the proposed vision-based control.

Figure 6 shows the trajectory of the road with guide lanes and the trace of the robot's travel. The road shown as the solid line has the curvature radius of 6 meters and the trace of robot is presented with the solid line and the black square in Fig. 6.

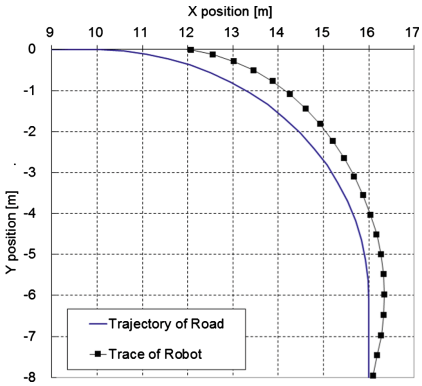

Fig. 6. Trajectories of robot's center on curved guide lanes with curvature radius of 6 meters.

Figure 7 shows the robot's steering angle during automatic driving in the simulation of Fig. 6. In Fig. 7, the command steering angle is determined from the neuro-fuzzy controller, the speed controller model, the steering controller model, and the robot model. The controller steers the robot to right (about −10[degree]) at right-turn curve, and to left (about +5[degree]) at left-turn curve. A lateral position error of the robot is defined as the difference between the center of the guide lanes and the center of the robot. As shown in Fig. 8, the driving is completed in lateral error less than 0.5[m].

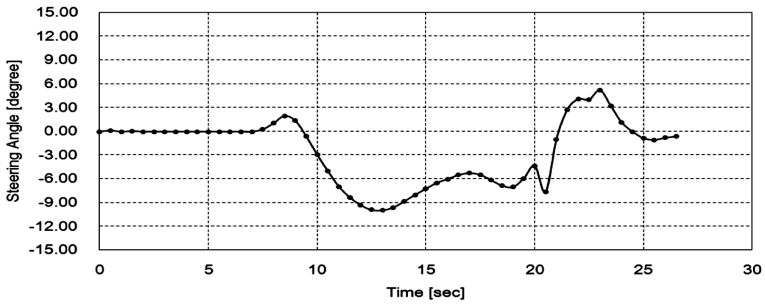

Fig. 7. Steering angle.

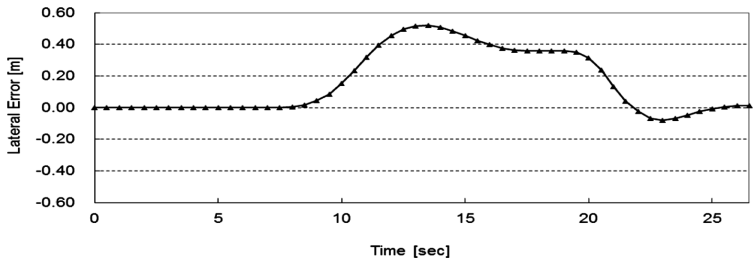

Fig. 8. Lateral position error of robot.

5 Experimental Driving Test

5.1 Setup of Vehicular Robot

The designed robot has 4 wheels, and its size is 1/4 of small passenger car. Driving torque comes from a DC motor set up the trans-axle of the rear wheel. Front wheel is steered by a BLDC motor. Energy source is two batteries connected directly, and each battery has 12 volts. And a camera is used as a vision sensor to get the road information. The control computer of the robot has function to manage all system, recognize the road direction from input camera image by road recognition algorithm, and make control signal of steering angle by the neuro-fuzzy control. And the control computer manages and controls input information from various signal, also it inspects or watches the system state.

The computer is chosen personal computer for hardware extensibility and software flexibility. Electric System to control is compose of vision system, steering control system, and speed control system. Vision system has camera to acquire road image and image processing to detect the guide lanes. Steering control system can convert from control value to analog voltage, read the current steering angle. Figure 9 shows the developed test robot.

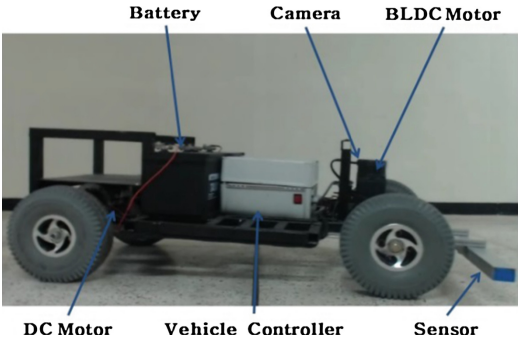

Fig. 9. Configuration of robot to test vision-based control.

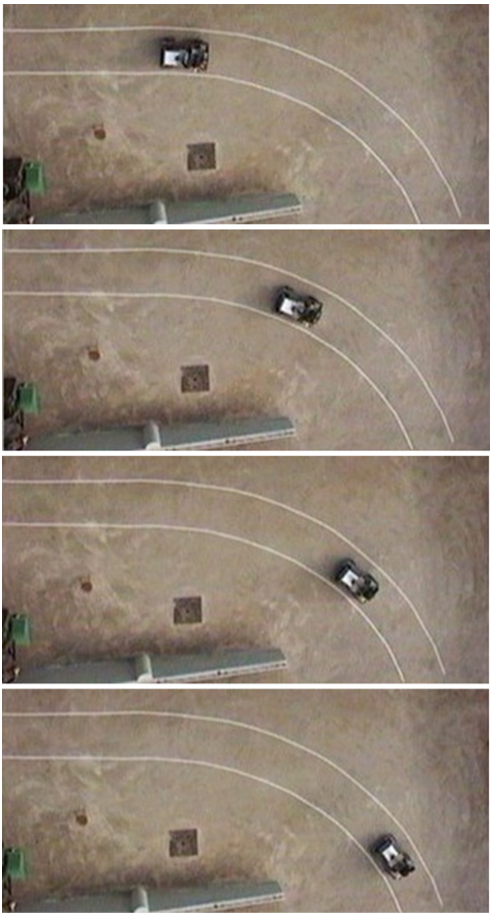

Fig. 10. Vision-based driving test on straight and curved lane.

5.2 Vision-Based Automatic Driving Test

The proposed vision-base control is tested as shown in Fig. 10. The guide lane's width is about one meter, and the length of the guide lane is set by 15 m with straight lane and curved lane. The curvature radius of curved lane is 6 meters. The robot is confirmed the excellent driving on the straight lane and the curved lane.

6 Conclusion

In this paper, a computer vision technology for a camera-based automatic guided robot was described using neuro-fuzzy control system. The nonlinear relation between the camera image and the control signals for the steering angle can be learned by neuro-fuzzy system. The validity of the proposed technology was confirmed by computer simulation. This approach is effective because it essentially replaces human's skill of complex geometric reasoning and control algorithm with a simple mapping of neuro-fuzzy system. This proposed method takes a much less calculation-intensive approach. The proposed control algorithm is available to be embedded in less expensive computer system because of reduction of network unit.

Acknowledgments. This research was financially supported by the Ministry of Science, ICT and Future Planning (MSIP) and Korea Industrial Technology Association (KOITA) through the Programs to support collaborative research among industry, academia and research institutes. (KOITA-2015-5); the Human Resource Training Program for Regional Innovation and Creativity through the Ministry of Education and National Research Foundation of Korea (NRF-2015 H1C1A1035841).

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