TELKOMNIKA, Vol. 11, No. 12, December 2013, pp. 7533~7538
e-ISSN: 2087-278X

Path Control Experiment of Mobile Robot based on Supervised Learning

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Abstract

To solve the weak capacity and low control accuracy of the robots which adapt to the complex working conditions, proposed that a path control method based on the driving experience and supervised learning. According to the slope road geometry characteristics, established the modeling study due to ramp pavement path control method and the control structure based on monitoring and self-learning. Made use of the Global Navigation Satellite System did the experiment. The test data illustrates that when the running speed is not greater than 5 m/s, the straight-line trajectory path transverse vertical deviation within ±20cm, which proved that the control method has a high feasibility.

Keywords: *mobile robot, slope path, supervised learning, driving experience, route control*

1. Introduction

At present, the robots which adapt to the complex working conditions are still in the research stage and there are so many problems to be solved. In the unknown and complex environments, the robot can not entirely predictable path [1-3]. To solve this problem, Schaal and Atkeson have proposed a method based on the model learning control. Kober and Peters proposed reinforcement learning method to make the robot imitate process reward-driven self-optimization [4], Bagnell proposed a machine learning method [5]. Guo Wei-bin and Chen Yong proposed robot navigation control based on fuzzy control [6]. Li Ke and Liu Wang-kai proposed Experts-fuzzy PID algorithm used for low-speed wind tunnel speed control [7]. Andrew. Ng and Pieter Abbeel come from Stanford University [8-9], who proposed the control method based on the self-learning not require the supervision of the instructors. Ruan Xiao-gang, Cai Jian-xian and Ren hong-ge from Beijing University of Technology proposed the bionic autonomous learning control algorithm [10-13]. The advantage of self-learning method through a certain learning mechanisms, such as the trial-and-error, a conditioned reflex, is interacted with the environment to achieve autonomy in an unknown environment optimization. This feature can reduce the unknown environment to the control system design difficulties. The literature [14] suggests that a combination based the Q learning theory and supervised learning control method applied to underwater robots. In short, for the location of the environment robot path control problem has been a lot of research, but the combination of monitoring and learning mechanisms control strategies are rare [15]. Supervision combined with self-learning control strategy combines the advantages of both the existing knowledge of the environment, control experience through interaction with the environment, to explore the optimal strategy in an unknown environment, for dealing with the unknown, complex environment robot control problems, with obvious advantages.

In this paper, it is used a combination of supervision and self-learning control strategy to try to resolve the autonomous mobile robot control problems in complex slope road autonomous driving. Because the path radius of the complex slope road changes greatly, and the downhill surface slope is unknown, so it has higher requirements on the control strategy. The control strategy is to build a control method based on learning mechanism, which is aimed to improve the ability to adapt to the unknown, complex environment. Taking account of the geometric characteristics of the roads and terrain features, it is proposed to improve the

Received June 27, 2013; Revised August 13, 2013; Accepted September 2, 2013

environment of the autonomous mobile robot adaptability based supervision-self-learning control algorithm. Supervision-self-learning control algorithm can be achieved the ramp traffic unmanned, intelligent, which can be able to improve transport efficiency, reduce transportation costs, have great significance and value in the field of military and transportation.

2. Control Strategy based on Supervised Learning

2.1. The Modeling of Ramp Pavement

It is described the slope road characterized by the geometric shape of the road plane, the vertical cross section geometry, the undulation of the road surface conditions. Road planar geometry consists of straight lines and curves, so the geometry of the road can be described by the curvature of the curve. Road Vertical curve include vertical grade and vertical curve. Considered the vertical curve radius generally longer, the road profile modeling is longitudinal slope. About the slope road modeling, the first is to establish coordinates of the road and the mobile robot, and to establish a conversion relationship between the roads coordinates and the mobile robot coordinates according to the position and attitude information of the mobile robot relative to the road. According to the coordinates of the edge of the markers, it determines the robot coordinates. It is used the vehicle sensors to receive the reference byisolation belt of the road on both sides, such as the green belt, the side of the road, as well as height and poor access to both sides of the road and road edge marker coordinates. According to finish the coordinate transformation, the coordinates of the markers in the coordinate system of the mobile machine can be converted to a road coordinate system. This combined with the characteristics of the road edge markers in the road coordinate system; the curvature of the curve of the road surface is designed to be a linear function of road length or a constant approximate calculation of the curvature of the curve of the road surface. The slope of the road can be calculated by car GPS/INS integrated navigation system to measure the pitch angle of the mobile robot. Road coordinates and the coordinates of the mobile robot are shown as Figure 1(a) and (b), reference to the traditional coordinate system, the X, Y and Z-axis of the road coordinate system is in the horizontal plane. The X, Y and Z-axis of the mobile robot road coordinate is parallel to the ramp surface. Road cross-section plot is shown as Figure 1(a), the mobile robot coordinate is changing with the transverse slope of the road, and its slope is φ. Road longitudinal section plot is shown as Figure 1(b), the mobile robot coordinate is changing with the longitudinal slope of the road, the slope of θ.

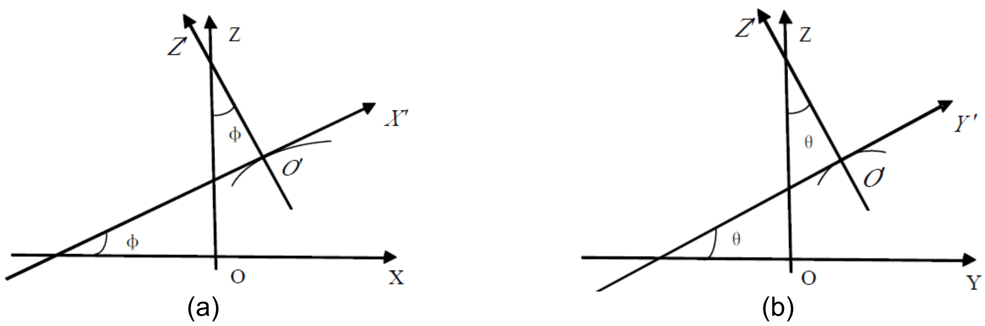

Figure 1. Road Cross-section Plot

While the mobile robot is moving, the undulation of the road surface will cause changes in the vertical plane of the coordinates of the mobile robot, so we can make use of the vertical acceleration of the mobile robot to reflect the changes in the road surface undulation. According to the longitudinal acceleration caused by the sample type of the known pavement characteristics do offline classification, to obtain the statistical characteristics of the classification process. Vertical acceleration is determined using the test method to determine, first select a similar road as the experimental site, and record the corresponding acceleration value given speed. The data is divided into a number of samples, using the method of principal component analysis, the data dimensionality reduction; use the linear discriminant analysis method to do classification to determine the best value.

2.2. Supervision Modeling based on Driving Experience

In the process of driving the car, the driver need to observe road conditions and the state of motion of the vehicle, make a judgment based on experience to control the steering and speed of the shift vehicle, complete a driving. During driving, the driver has the flavor experience; the experience can be as autonomous robot control data, with similar driving model to control the robot. Driving empirical data accumulated in the driver's day-to-day driving course, driving experience as a learning sample input model, the robot learned enough driving experience. Taking into account the characteristics of the driver driving experience, the robot driving experience model was built by fuzzy control and neural network. In accordance with the hierarchical structure of the fuzzy logic operation step, the model endues the fuzzy system with neural network learning function. The model input signals have 5, there are the road centerline lateral error of mobile robot, mobile robot heading angle and road tangential direction of the angle, the speed of the mobile robot, the curvature of the road plane linear, mobile robot yaw rate. The output signal is a steering wheel angle of the mobile robot. The first hidden layer of the model is the fuzzy layer, each state is transformed into fuzzy set, and each neuron input fuzzy subset. Second hidden layer fuzzy rule layer, each neuron represents a logical operator; third hidden layer fuzzy decision process. The structure is shown in Figure 2. It is used the gradient descent algorithm to train the neural network weights. Speed of decision-making module can achieve similar neural network structure.

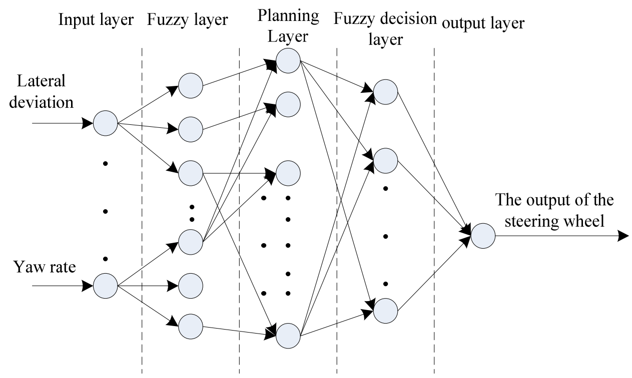

Figure 2. Neural Network Model

2.3. Based on Self-Learning Control Method

To achieve the learning control of mobile robots, it is used the reinforcement learning algorithm based on the execution-evaluation (Actor-Critic). Execution-Evaluation learning framework has two main units: the operation selection unit and the operation evaluation unit. In the learning process, the two units of the policy function and value function of the Markov decision processes do approximation. In order to achieve the approximation of the value function and the policy function, and improve the generalization ability of the learning process, it is made use of neural networks to approximate the value function and the policy function of the learning process. The structure of the algorithm is shown in Figure 3.

Fuzzy neural network shown in Figure 2 as a model of action selection unit will reflect the extent of the merits of the selected action TD error as a reinforcement signal involved in the update process of the strategy of neural network weights update algorithm uses the gradient descent-based method. RBF neural network as a model of the action evaluation unit, the unit of value function approximation and calculation of secondary reinforcement signal. First design a reasonable return function calculation, which is to strengthen the key to the success of the learning algorithm. It should be considered of the accuracy of the autonomous mobile robot to follow the road, driving stability, ride comfort and performance, to make sure the reward function. By the above method, it is achieved by follow the path and speed of decision-making on-line self-learning.

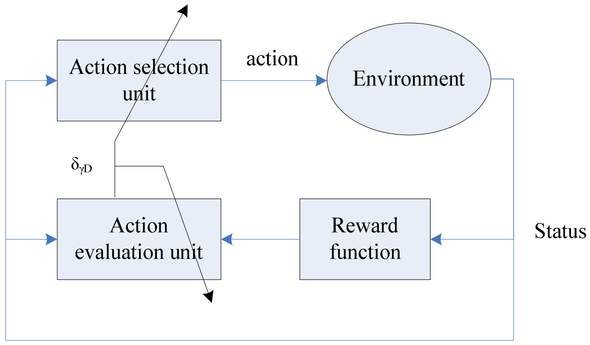

Figure 3. The Actor-critic Algorithm Structure

3. Control Structure based on Supervised Learning

Supervision and strengthen learning fusion control system structure is shown in Figure 4. The control output is mainly composed of two parts, based on reinforcement learning to control the output signal and the output signal based on supervised learning control.

Supervised learning and reinforcement learning to interact via two ways: the implementation of control tasks, offline learning sample data using accumulated training action selection module neural network, the action selection module fully learn from the control experience accumulated in the offline data; task in the implementation of control receiving a higher return function value, that is the ideal control results, and the data for training actions neural network module entry learning sample data for future use.

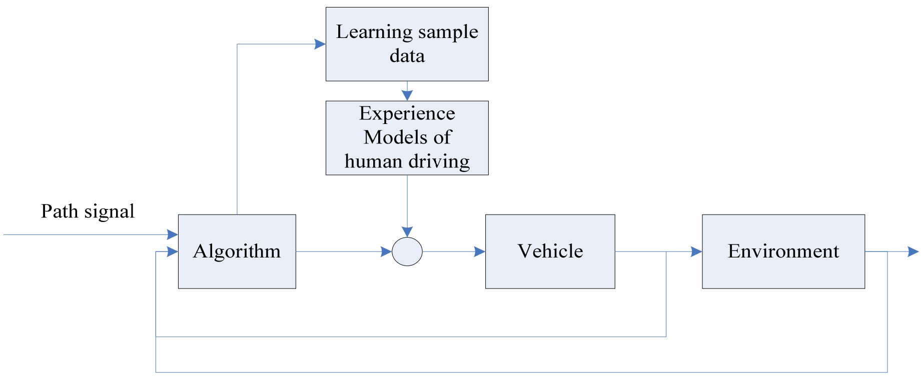

Figure 4. Control Structure based on Supervision and Reinforcement Learning

4. Experiments

4.1. Path Map Reconstruction Experiments

Mainly by the laser positioning scanner NAV200 probe positioning experiment based on the roads surrounding environment, in order to be able to scan to the road surface, the laser scanner detects the distance and the scanning resolution, respectively 20m and 0.5° scanning angle range of 180°.

Using the laser scanner to detect signal acquisition, and data parsing and feature extraction, the map reconstruction path environment. The experimental results are shown in

Figure 5. Can be seen from the figure to clearly show the path on both sides of the marker, can be well determine the running path of the robot, the path map is better reproducibility.

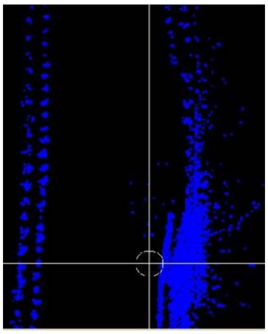

Figure 5. Sick Detect Environmental Test Results

4.2. Road Testing

In order to verify the effect of the control algorithm, it is used the four-wheel vehicles as the test vehicle of a mobile robot, made use of the Global Navigation Satellite System (GNSS) and laser positioning scanner to measure, used Global Navigation Satellite System (GNSS) to complete a wide range of positioning, made use of laser positioning triangulation to complete the precise positioning and conducted experiments shown as Figure 6 by using supervised learning control method. The maximum speed is limited to 5m/s, and the experimental results show the lateral follower deviation ±0.2m (RMS), relatively roads heading angle deviation of 10° (RMS), the speed control error of 1m/s (RMS), the sentinel parking error 0.1m (RMS).

While the robot straight line running, transverse vertical trajectory and path deviation disabilities 20cm, which can meet the robot along the path of the run and dock. Because the installation error between Laser scanner rotational center and the robot motion center, the robot pivot turn control accuracy, the relative sliding between the tire and the ground while the robot pivot turning and other factors, the operation of the robot path may exist a certain deviation, which does not affect the operation of the robot and docked.

Figure 6. Path Followed Experiments

5. Conclusion

It is used a combination of supervision and self-learning control strategy to resolve the autonomous mobile robot control problems. According to study on changes in the slope road plane features, it is proposed the robot adaptive path control method based on the driving experience and the supervised learning. And also, it is carried out a detailed analysis of slope road geometry characteristics, used fuzzy neural network control algorithm to construct the supervised learning model based on the driving experience. Through doing the experiments by using the global Navigation Satellite system (GNSS) and laser positioning scanner, it is achieved the control in the slope continuous curve and a straight path to follow. The experimental results show the feasibility of the method, but for the environment temperature and humidity and climate change and other factors on the control system, as well as the stability of laser navigation system to work long hours, can also be studied in depth.

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