The Trace Algorithm of Mobile Robot System Using Neural Network

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Abstract: In this paper, we propose the self-autonomous algorithm for mobile robot system (MRS). The proposed mobile robot system which is learned by learning with the neural network can trace the target at the same distances. The mobile robot can use ultrasonic sensors and calculate the distance between target and mobile robot. By learning the setup distance, current distance and command velocity, the robot can do intelligent self-autonomous drive. We use the neural network and back-propagation algorithm as a tool of learning. As a result, we confirm the ability of tracing the target with proposed mobile robot.

1. Introduction

Lately, mobile robot has been developed. The AIBO that is a pet robot shaped like dog by the Sony company and the ASIMO that is a human style robot by the Honda company have wide expanded of the concept of robot used in existent industrial world as see thing that robot is chosen by one of promising interest skill of 10 and main research of the 21th century.

This paper will wish to introduce neural networks theory by methodology to control MRS. It can calculate the distance between target using ultrasonic sensors about some particular target that wide expand in simplicity drive of the existing mobile robot. It calculates the present velocity for target after set up the target at the same distance.

A common MRS can trace target at static environment at regular intervals using some simple rules. On the other hand, the proposed MRS can trace target and reduce the error rate at the more dynamic environment using soft computing such as neural network. The MRS recognizes voice command by each protocol. And also, it can trace a specific target that keeps the same distance as driving self-autonomous state. In this paper, we use the variation of distance and position of MRS and control MRS with them at real time. An introduction of the principle control for MRS is as follows.

The MRS detects surrounding obstacles and the target with ultrasonic sensors every 0.08 second. Finally, the MRS normalizes 5 sensor data and averages those considering inaccuracy of sensor at that time. Particularly, the MRS estimates the distance with target using 1, 2, 12-th top portion sensor department of mobile robot and then gets the minimum distance. The MRS calculates direction and velocity of moving target using neural networks and then set the next velocity of the MRS. Considering of load during the MRS operates, the velocity is increased or decreased continuously with the flag value. Also, if the distance of between the MRS and the target is equal to the set distance then there is no more change of the velocity according to the flag value. In the MRS, the flag value takes a role of decision such as preserving the velocity or the distance. By the flag value, if the MRS once stops the change of velocity or distance, in the next time, the MRS can choose the timing of change of velocity or distance again.

In the main discourse, we explained system principle and a characteristic of motion for MRS use in this work. Also, we researched the algorithm about neural network that gives intelligence techniques to the MRS. We described the result of mobile robot using neural network. Finally, we investigated result about the work in a conclusion.

2. Structure of the MRS

Mobile robot that is USB robot control system used in work has notebook computer for control of MRS, USB camera and 12 ultrasonic sensors. The MRS operates with three motors that are asynchronous and make driving and steering operation independently or dependently. The same power is provided to each wheel. The controller for motor is PID controller. The MRS has 2 USB motor controller board and USB ultrasonic range finder board for control 24 ultrasonic sensors. The controller that is designed to composition of USB Robot-Controller is USB motor controller and USB ultrasonic range finder.

The USB motor controller is board that is integrated by motor for PID control, servo-amp, USB interface, absolute encoder-input port of 10 bit and I/O port of 5 bits. Also, it is possible to control location and velocity. Also, The USB ultrasonic range finder can drive maximum 12 ultrasonic sensors. It can drive and select priority order of ultrasonic sensor according to maximum distance. If the USB motor controller becomes plug in USB terminal board of a computer, motor control is available immediately without additional setting. The USB motor controller used PID control way. The USB ultrasonic range finder has 50 KHz Driving-Frequency. It has distance information in surrounding of MRS as having intention special quality of 15 degrees.

3. Multilayer Neural Network and Learning Algorithm

We investigated theory of neural network that used technique for control MRS to trace target and learning algorithm used in work. Neural network that imitate human's brain structure is consisted of dispersion memory element of analog called synapse that combines many operators called Neuron. The basic arithmetic component of neural network is multiple inputs and multiple outputs. The synapse operator offers sum about past experience (w_i) and neuron input (x_i) and the soma operator is performed operation inner part of neuron cellular. Also, it is realization to operation of sum. The figure 1 shows multilayer neural network that has hierarchic structure which is hidden layer more than one exists between input layer and output layer. The multilayer neural network is feedfoward network that has no direct connection of input layer from output layer and the inner parts of the connection in each layer. The equation 1 shows the output of multilayer neural network.

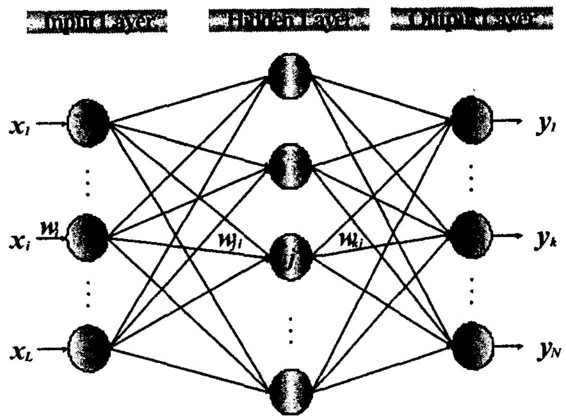

Figure 1. Structure of the multi layer neural network

$$
\begin{aligned}
y_k &= f_k^O\left(\sum_{j=1}^{M} x_j^H \circ w_{kj}^O\right) \\
&= f_k^O\left(\sum_{j=1}^{M} f_j^H\left(\sum_{i=1}^{L} x_i^I \circ w_{ji}^H\right)\circ w_{kj}^O\right) \\
&= f_k^O\left(\sum_{j=1}^{M} f_j^H\left(\sum_{i=1}^{L} f_i^I\left(x_i \circ w_i^I\right)\circ w_{ji}^H\right)\circ w_{kj}^O\right)
\end{aligned} \tag{1}
$$

where f_i^I, f_k^O, f_j^H are nonlinear activation functions of each input layer, hidden layer and output layer. w_i is input weight that do normalized signal. w_{ji}^H, w_{kj}^O is weight between input layer and hidden layer, between hidden layer and output layer respectively. The back-propagation learning algorithm, supervised learning method, is easy realization as reinforcement learning method. Also, it has good ability of learning. Then, this is learning method used much to the multilayer neural network. The back-propagation learning process is like as following, and learns using all error sums of differences between neuron' s output and target value in each output layer.

$$E = \frac{1}{2}\sum_{k=1}^{N}(y_{dk} - y_k)^2 \tag{2}$$

where y_{dk}, y_k is target value of k-th neuron and output value of k-th neuron. Change amount of weights in output layer to reduce error is using gradient descent and chain rule. We can get equation 3, 4.

$$\Delta w_{ji} = -\eta\frac{\delta E}{\delta w_{ji}} = -\eta\delta_j x_j \tag{3}$$

$$\Delta w_{kj} = -\eta\frac{\delta E}{\delta w_{kj}} = -\eta\delta_k y_k \tag{4}$$

The error signal of each layer transmitted to backward is next equation 5, 6

$$\delta_k = (y_{dk} - y_k)f'(\lambda, u_k) \tag{5}$$

$$\delta_j = f'(\lambda, u_j)\sum_{i=1}^{L}\delta_k w_{kj} \tag{6}$$

where η is the learning rate, and $f'(\cdot)$ is sigmoidal activation function. u_j, u_k are total sums of input for hidden layer and output layer respectively. New weights of each layer can be taken equation 5 and 6. They are adjusted to equation 7 and 8. A α is moment term.

$$w_{ji}(t+1) = w_{ji}(t) + \Delta w_{ji} + \alpha\left[w_{ji}(t) - w_{ji}(t-1)\right] \tag{7}$$

$$w_{kj}(t+1) = w_{kj}(t) + \Delta w_{kj} + \alpha\left[w_{kj}(t) - w_{kj}(t-1)\right] \tag{8}$$

If new weights of each layer are repeatedly using the learning rate and activation function from output layer to input layer, output error of each neuron are on the decrease. Finally, last output value of neural network is reached in target value.

4. The Trace Algorithm of MRS Using Neural Network

The proposed algorithm is designed according to the one of features of the MRS. A considered feature is that the MRS receives current distance values for the target with ultrasonic sensors. These values are stored in the memory with the values of next time and the MRS uses all stored data for deciding the velocity. Finally, the MRS can get current direction and velocity of the target from the equation 9 using the past distance value, the current distance value and the velocity of robot.

$$V = (D_A + 10\times\pi\times Time\times V_B - D_B)/(10\times\pi\times Time) \tag{9}$$

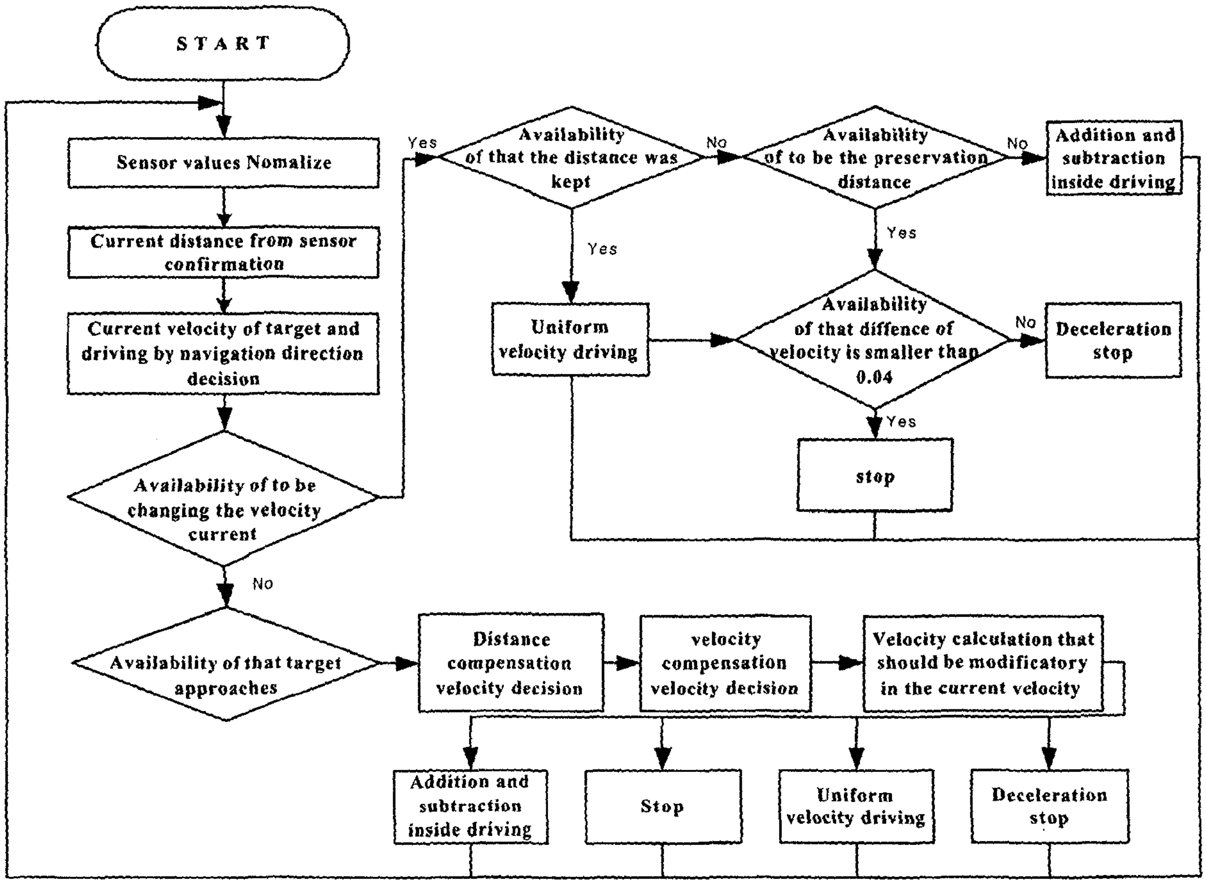

Figure 2. Flow Chart of Learning Rule

V : Current velocity of trace target

D_A : Past distance between the MRS and the target

V_B : Past velocity of the MRS

D_B : Current distance between the MRS and the target

The term ' $10\times\pi$ ' is that can convert absolute velocity being measured with ' rps' dimension to companion velocity of the MRS. If the result of equation 9 shows negative or positive we make the value, change 0 or 1, respectively and this is for calculation of the next data.

To decide driving velocity, we are emphasis on two decisions of compensation velocity by distance and velocity. First, compensation velocity by distance is for preserving distance with the target. Second, compensation velocity by velocity is for reduction of the velocity margin. In the MRS, the velocity is first compensated by the distance and if the MRS traces the target at regular intervals then, compensated by velocity to keep the current state. The figure 2. is flow chart of learning rule.

$$V_{d.c} = (D_n - D_c) \qquad (10)$$

$V_{d.c}$: The distance preservation compensation velocity

D_n : Current the distance

D_c : Before distance

The equation 2 shows the compensation velocity by distance Output of algorithm displays whether the velocity is changing, whether the other velocity must be applied and whether the velocity of the MRS changes from current value to limit to trace the target. The target of our work is to show whether the neural network algorithm can learn the amount of the velocity variations using 3 inputs. We expressed the block diagram in the figure 3.

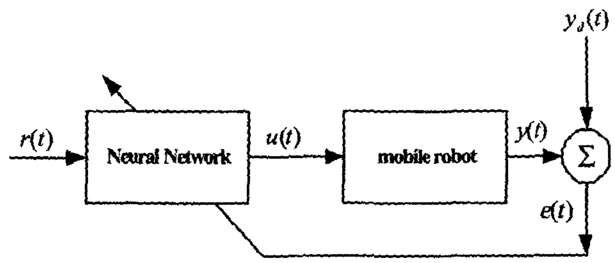

Figure 3. The block diagram of system

The 3 inputs of neural network are current distance between the MRS and target, difference between the current velocity of the target and past velocity of the MRS, and the variable ' change'.

In the neural network, the number of hidden neuron is 20, activation function is a hyperbolic tangent and learning rate is 0.016. The back-propagation algorithm is used to for weight update and the data for learning is 1600 survey data and the iteration for learning is 100000 times.

5. Performance Work Result of The MRS

The following figure 4. shows comparison between the survey data and the data using neural network.

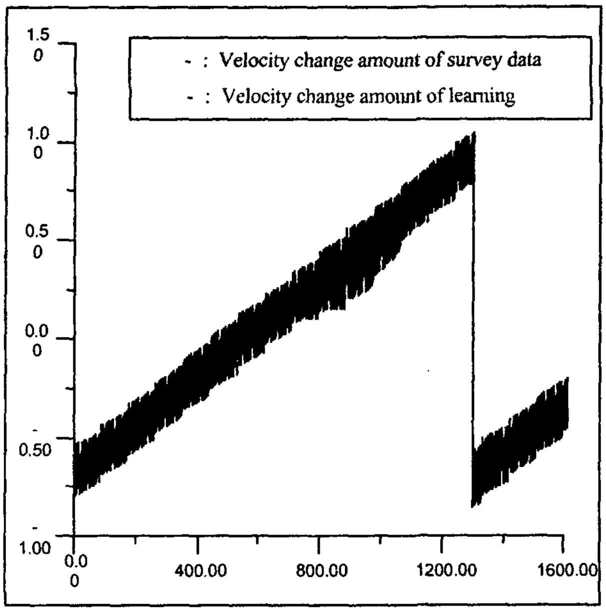

Figure 4. The Results of Simulation

6. Conclusion

So far, trace algorithms for MRS designed to drive mobile robot in low speeds of 10 to 20 percents of the driving capacity.

In this paper, the proposed algorithm showed that MRS keeps the distance while tracing the target with the speed above 40 percent of the driving capacity, as long as the velocity of the target is within the absolute velocity of the robot. The result of the simulation showed that the proposed MRS is more robust to the dynamic environments compared to the common MRS.

For the future work, the algorithm which enables tracing of the mobile robot with more ultrasonic sensors for the unexpected environment such as the linkage could be studied.

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