Neural Network Based Guidance Control of a Mobile Robot

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Abstract : In this paper, the position control of a car-like mobile robot using neural network is proposed. The positional information of the mobile robot is given by a laser range finder located remotely through wireless communication. The heading angle is measured by a gyro sensor. Considering these two sensor information as references, the robot posture by localization is corrected by a cascaded controller. In order to improve the tracking performance, a neural network with a cascaded controller is used to compensate for any uncertainty in the robot. The remotely located neural network filter modifies the reference trajectories to minimize the positional errors by wireless communication. A car-like mobile robot is built as a test-bed and experimental studies of proposed several control algorithms are performed. It turns out that the best position control can be achieved by a cascaded controller with neural network.

Keywords: Mobile robot, neural network, cascaded controller, reference compensation technique

1. INTRODUCTION

A mobile robot has been quite attractive in robotic research area due to its mobility to move in anyplace. Autonomous navigation and control is the key issue in the mobile robot research area. In order to achieve autonomous navigation, the performance of a mobile robot control is often dependent upon the accuracy of sensors. The mobile robot relying on local sensors such as a gyro sensor and an encoder sensor can undergo the dead-reckoning situation [1]. To avoid dead-reckoning situation, the reference sensor is absolutely needed with suitable sensor fusion algorithms. The reference sensor is not the sensor attached to the robot but the sensor located out of the robot to give global attitude information of the robot. Broadly speaking, GPS or LBL(Long Base Line) can be used as a reference sensor. A precise GPS can be used above the ground and an LBL can be used under the sea. But all of two sensors are very expensive.

Having reliable sensors available, states of the mobile robot have to be estimated before they are controlled. Popular state estimation algorithm is known as the Kalman filter. Many researches of autonomous navigation have been done based on the Kalman filtering method [2-4].

Tracking control algorithms of mobile robots have been proposed as well. Tracking control of a mobile robot can be folded into two categories depending upon what kind of mobile robot models are used: kinematics or dynamics. Dynamic model based control methods have been proposed to consider dynamic behaviors such as slips [5]. Since dynamic effects of the mobile robot can be minimized by structural changes, most of mobile robot tracking controls have been conducted based on kinematic model of it [6-10]. Kinematic models of mobile robots ignoring dynamic conditions are generally defined as global coordinates such that the control laws minimize global position errors. Backstepping control method guarantees the stability based on the Lyapunov function [6-7]. Cascaded control method is a simplified version of backstepping control method [9]. Specially for the mobile robot tracking control, cascaded control is so simple that implementation can be done with ease.

In our previous researches, visual servoing control of a mobile robot has been done [10]. Vision information is used as feedback signals, and neural network is used to correct the tracking error of dead-reckoning robot. Among various control algorithms, it has been verified that neural network controller has shown the best performance [10]. However, use of camera as a reference sensor limits the terrain of the mobile robot.

In this paper, as an extension of our previous researches, new concept of guidance control by using neural network is proposed. Neural network with the reference compensation technique is used to guide of the mobile robot to the goal position. Instead of using a vision sensor, tracking of a mobile robot is corrected by correction signals from neural network based on the laser finder sensor information.

The reference compensation technique (RCT) is known as one of on line learning algorithms for neural network. Real application examples of the RCT can be found in the our previous researches [11]. Here we extend the idea of the RCT to the mobile robot tracking control that is totally disconnected from neural controller and controlled by wireless communication.

2. KINEMATICS AND EROR EQUATION OF MOBILE ROBOT

The tracking control for a mobile robot is to find appropriate control laws that make the tracking error converge to zero. Since a mobile robot can be modeled as a simple inertial system, the controller based on kinematics rather than dynamics [10]. The controller based on kinematics controls forward velocity v and the angular velocity w independently by motors.

Let (x, y) denote the coordinates of the center of mass, and θ the angle between the heading direction and the x axis. We assume that the wheels do not slide, which results in the following equations

$$\begin{aligned} \dot{x} &= v \cdot \cos\theta \\ \dot{y} &= v \cdot \sin\theta \\ \dot{\theta} &= w \end{aligned} \tag{1}$$

where the forward velocity v and the angular velocity w are considered as inputs. The no-slip condition imposes the non-holonomic constraint

$$\dot{x}\sin\theta - \dot{y}\cos\theta = 0 \tag{2}$$

Assume that a feasible reference dynamics $(x_r, y_r, \theta_r, v_r, w_r)^T$ is given, dynamics satisfies the following equations

$$\begin{aligned} \dot{x}_r &= v_r \cdot \cos\theta_r \\ \dot{y}_r &= v_r \sin\theta_r \\ \dot{\theta}_r &= w_r \end{aligned} \tag{3}$$

where v_r and w_r are considered as reference inputs.

For solving the tracking control problem based on kinematic models, the following global coordinate transform is needed. [8].

Assume that reference trajectories (x_r, y_r, θ_r) are given, an error dynamics is as follows.

$$\begin{bmatrix} x_e \\ y_e \\ \theta_e \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta & 0 \\ -\sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_r - x \\ y_r - y \\ \theta_r - \theta \end{bmatrix} \tag{4}$$

Figure 1 shows the coordinate transform for error equation.

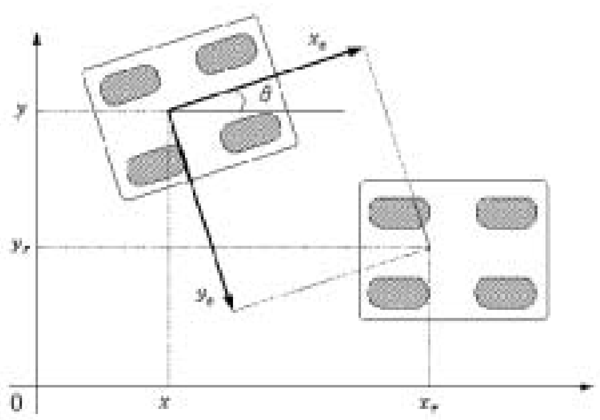

Fig. 1 The new error coordinates.

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This global transformation of co-ordinates makes the error variables become independent from the choice of the inertial coordinate frame. Based on these new coordinates the tracking error dynamics becomes as following equations.

$$\begin{aligned} \dot{x}_e &= w y_e - v + v_r(t)\cos\theta_e \\ \dot{y}_e &= -w x_e + v_r(t)\sin\theta_e \\ \dot{\theta}_e &= w_r(t) - w \end{aligned} \tag{5}$$

The tracking control problem is to find appropriate control laws for v and w such that the tracking error $(x_e, y_e, \theta_e)^T$ converges to zero.

3. CASCADED CONTROLLER

Here we use the cascaded controller to achieve globally uniformly asymptotically stable tracking of the mobile robot Cascaded systems are composed of subsystems. If a state of a subsystem is assumed to converge to zero. The remaining subsystem is simplified, and cascaded controllers are designed to make subsystems uniformly asymptotically stable. Considering equation (5), one input is used for stabilization of a subsystem in equation (5). By means of the input w the last dynamics in equation (5) can easily be stabilized by defining the control law as

$$w = w_r(t) + k_1\theta_e \tag{6}$$

Equation (6) results in the globally uniformly exponentially stable subsystem as follows

$$\dot{\theta}_e = -k_1\theta_e \qquad k_1 > 0\,. \tag{7}$$

Substituting equation (6) into (5) yields the remaining dynamics as

$$\begin{aligned} \dot{x}_e &= w_r(t)y_e + k_1\theta_e y_e - v + v_r(t)\cos\theta_e \\ \dot{y}_e &= -w_r(t)x_e - k_1\theta_e x_e + v_r(t)\sin\theta_e \end{aligned} \tag{8}$$

Assume that the stabilization of θ_e has been established. Substituting $\theta_e(t) = 0$ into (8)leads to the following simplified equation.

$$\begin{bmatrix} \dot{x}_e \\ \dot{y}_e \end{bmatrix} = \begin{bmatrix} 0 & w_r(t) \\ -w_r(t) & 0 \end{bmatrix} \begin{bmatrix} x_e \\ y_e \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} \begin{bmatrix} v_r(t) - v \end{bmatrix} \tag{9}$$

If $w_r(t)$ is persistently excited, then the control law becomes

$$v = v_r(t) + k_2 x_e - k_3 w_r(t) y_e \qquad k_2 > 0, \qquad k_3 > -1 \tag{10}$$

This makes the resulting closed-loop system of equation (7) and (9) be globally uniformly exponentially stable. Cascaded controller has a nice structure in the tracking error dynamics, that makes the nonlinear tracking problem be reduced to sub linear systems.

4. PROPOSED CONTROL ALGORITHMS

4.1 Control law 1 : cascade control based on encoder

The robot is controlled by the cascaded controller. The reference trajectory of the robot is generated by transformation from cascaded controller that uses errors from encoder signal . In fig. 2, the block diagram of the cascade controller that transforms the errors from present coordinates of robot, x, y, θ as inputs to the outputs v, w as control inputs.

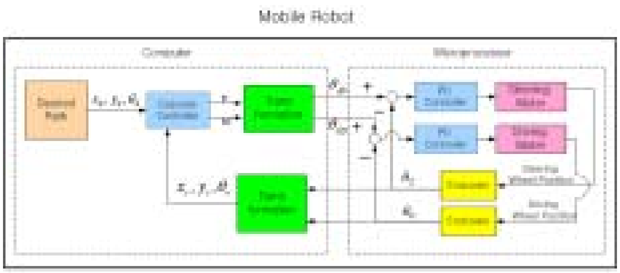

Fig. 2 Cascaded control based on encoder

The x_r, y_r, θ_r are actual moving values of the robot and they are measured from encoder sensor outputs. These values are also used to calculate tracking errors as inputs of a cascade controller. The cascade controller outputs, v and w, are transformed to desired attitude of robot using coordinate transformation, then used as input signals for PD controller. The control laws are as follows.

$$\begin{aligned} w &= w_r(t) + k_1\theta_e \\ v &= v_r(t) + k_2 x_e - k_3 w_r(t) y_e \end{aligned} \tag{11}$$

Here, $x_e = x_d - x_r$, $y_e = x_d - x_r$, $\theta_e = \theta_d - \theta_r$, k_1, k_2, k_3 : control gains, w_r : desired angular velocity , v_r : desired linear velocity, θ_e : heading angle, and θ_r : actual angular displacement transformed form encoder data. As a result, the dead-reckoning happens due to dependence of encoder for robot position.

4.2 Control law 2 : Cascaded control based on laser finder

The fig. 3 shows the block diagram of a cascaded controller using an external laser finder information. The information from an external laser sensor supplies accurate absolute position information on x, y and θ for a mobile robot. The position and attitude information of the robot are used as input for a cascade controller. The internal control loop is PD control based on encoder signals.

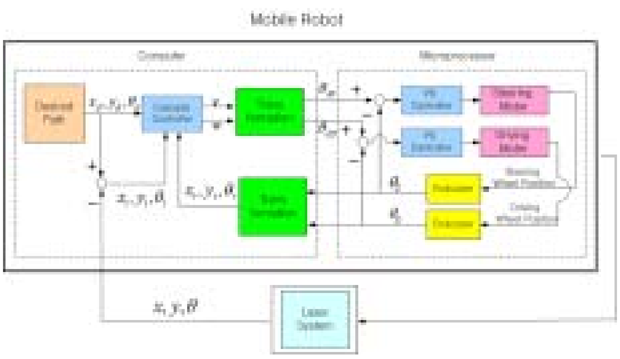

Fig. 3. Cascade control based on laser finder

The present attitude information of the robot is obtained by laser scanner, and then transferred to robot after modifying the attitude to be achieved.

$$\begin{aligned} w &= w_r(t) + k_1\theta_l \\ v &= v_r(t) + k_2 x_l - k_3 w_r(t) y_l \end{aligned} \tag{12}$$

Here, $x_l = x_d - x$, $y_l = y_d - y$, $\theta_l = \theta_d - \theta$ represents error between desired coordinate information and position information achieved form the laser finer. The above equation uses error signal used by laser information of control law 1, this error term reduces tracking error due to the dead-reckoning of the robot.

4.3 Control law 3 : neural network control

The control law 3 is supplemented with neural network in control law 2 and shown as fig. 4.

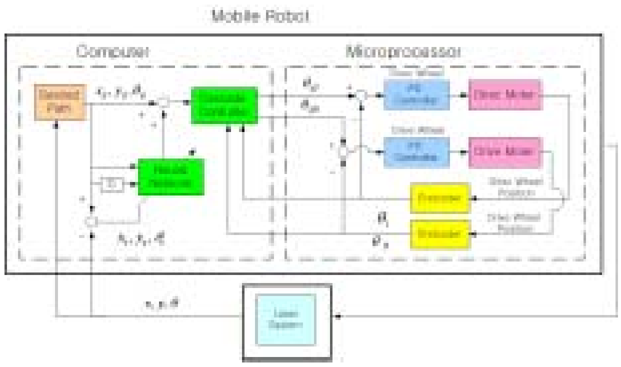

Fig. 4. Cascaded + neural network control based on laser finder

In this control mode, the output of neural network is added on input of control law 2 to compensate for errors caused due to uncertainties. The control laws are given as

$$\begin{aligned} w &= w_r(t) + k_1(\theta_e + \theta_{le}) + N_w \\ v &= v_r(t) + k_2(x_2 + x_{le}) - k_3 w_r(t)(y_e + y_{le}) + N_v \end{aligned} \tag{13}$$

Here N_w and N_v are the output of neural network. For on-line learning of neural network, it is important to define the learning signals. The learning signals are defined as following error form

$$tn = k_p p_{le} + k_{dp}\dot{p}_{le} + k_\theta \theta_{le} + k_{d\theta}\dot{\theta}_{le} \tag{14}$$

Here $p_{le} = \sqrt{x_{le}^2 + y_{le}^2}$, $\theta_{le} = \theta_d - \theta$. In order to make the learning signal converge to zero, the objection function is defined as follows.

$$E = \frac{1}{2} tn^2 \tag{15}$$

Differentiating (15) yields

$$\frac{\partial E}{\partial w} = tn \frac{\partial tn}{\partial w} \tag{16}$$

The gradient method is used to apply back-propagation algorithm.

$$\Delta w(t) = \eta \frac{\partial E}{\partial w} v + \alpha \Delta w(t-1) \tag{17}$$

$$w(t+1) = w(t) + \Delta w(t) \tag{18}$$

where η is a learning rate, α is a momentum.

5. EXPERIMENTAL RESULTS

5.1 Experimental environment

The mobile robot uses four kinds of sensors such as a ultrasonic, an encoder, a gyro and a laser finder sensor. The laser finer serves as absolute sensor. The ultrasonic sensor is in environment of relative distance between robot and surrounding objects. The gyro and encoder sensors do important roles to estimate local position of the mobile robot. The ultrasonic sensor is used to prevent collision with surrounding objects. The fig. 5 shows main control window of the mobile robot. Sensed information is displayed.

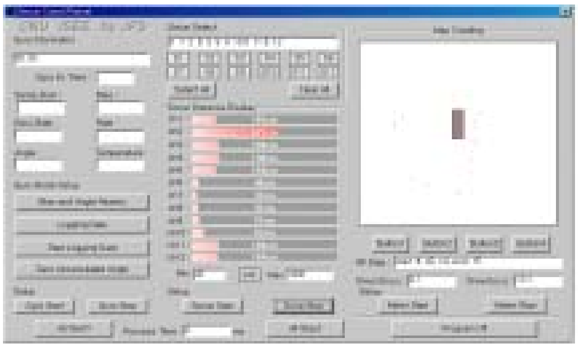

Fig. 5 Main Control Program windows of mobile robot

Figure 6 shows the developed car-like robot.

Fig. 6 Mobile robot

Figure 7 shows the laser finder sensor system remotely located from the robot.

Fig. 7 Laser finder

The laser finer system transmits a reference coordinate of the mobile robot to the mobile robot by the wireless communication by every sampling cycle.

5.2 Experiment 1 : Tracking

The initial robot position is set as heading angle of 36 deg and located at distance of 11m.

5.2.1 Cascade controller with gyro (Control law 1)

Control performances by a cascaded controller relying on encoder measurements are shown in figures 8 and 9. Global position error can not be corrected , and the heading angle of the mobile robot is bounded within 1~2deg .

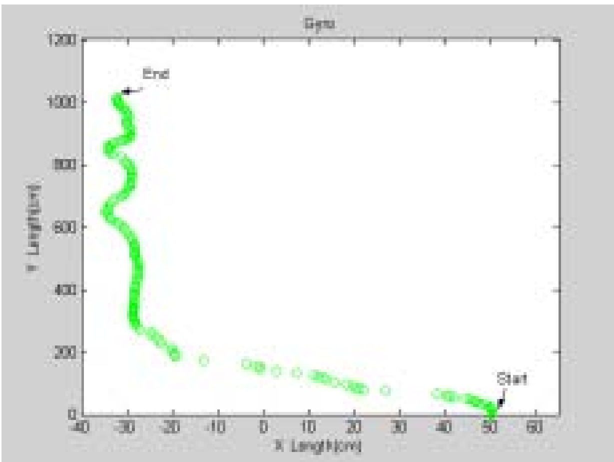

Fig. 8 Position tracking result with control law 1

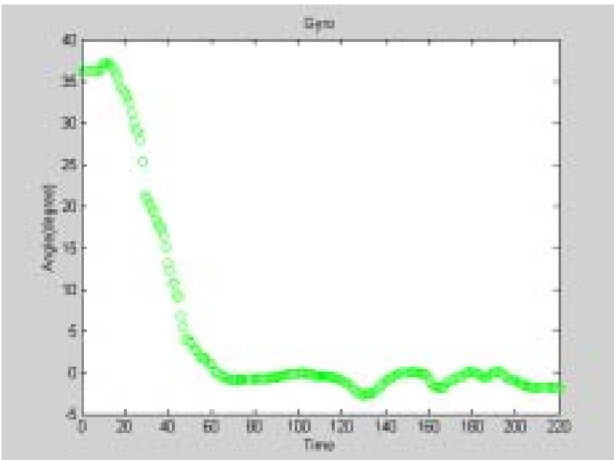

Fig. 9 Heading angle result with control law 1

5.2.2 Cascade controller with gyro and laser finder (Control law 2)

The resulting performances of a cascaded controller with laser sensor information are depicted in figures 10 and 11. Global position error and heading angle can be corrected with laser finder's information. The initial heading angle error is 35 deg.

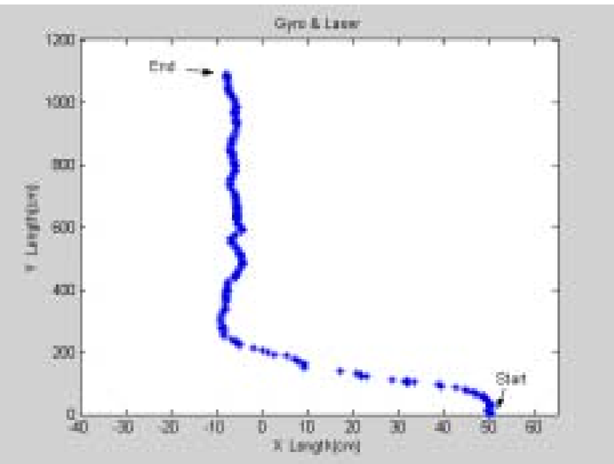

Fig. 10 Position tracking result with control law 2

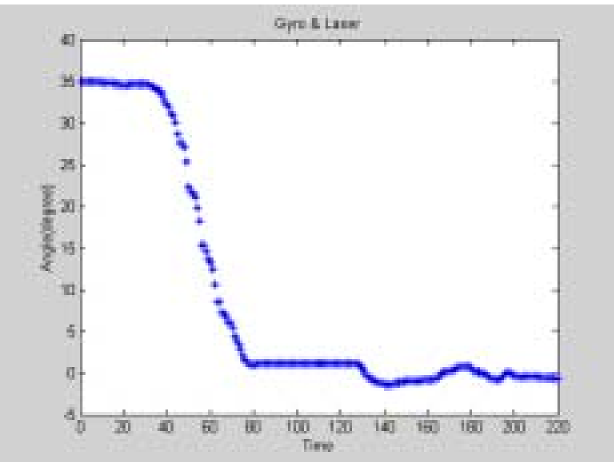

Fig. 11 Heading angle result with control law 2

5.2.3 Neural network controller with gyro and laser finder(Control law 3)

When neural network is added to the cascaded controller, performances are much improved. Attitude error of mobile robot is decreased, and the position error converges to 0 as shown in fig. 12. The initial heading angle is set as 36.5 deg.

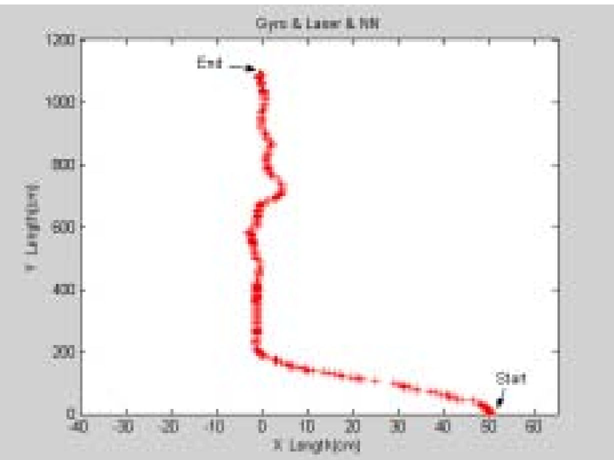

Fig. 12 Position tracking result with control law 3

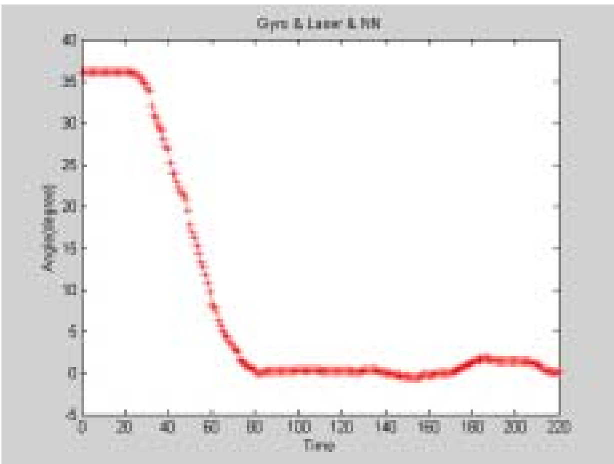

Fig. 13 Heading angle result with control law 3

In order to clearly compare the performances of each control algorithm, all tracking are plotted in figure 13. it is clear that neural network controller shows is the best tracking result among those control algorithms.

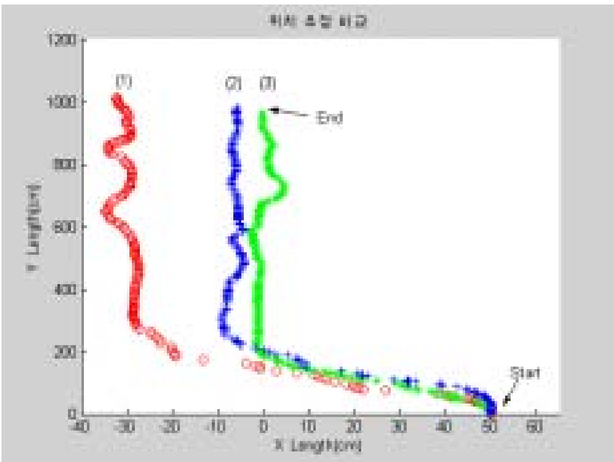

Fig. 14 Tracking result compared with control law

5.3 Experiment 2: Traveling on the sand

Another interesting tracking task has been conducted. The robot is required to move on sand so that slipping situation happens. Fig. 15 depicts experimental environment that can cause the wheel slip.

Fig. 15 Experiment traveling on the sand

The experimental results are shown in figure 16. As expected, neural network controller shows the best performance.

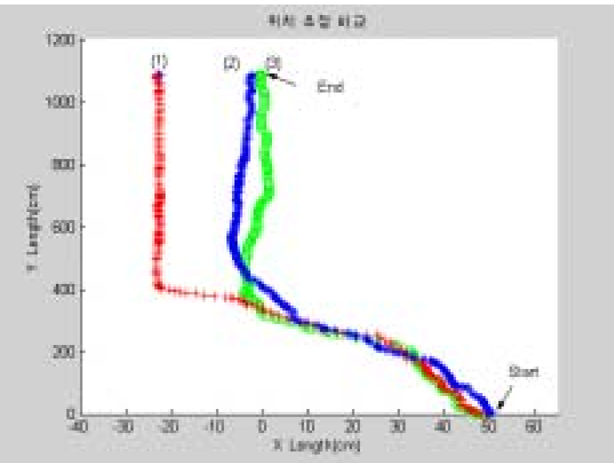

Fig. 16 Position tracking results with compared with control laws(slip condition)

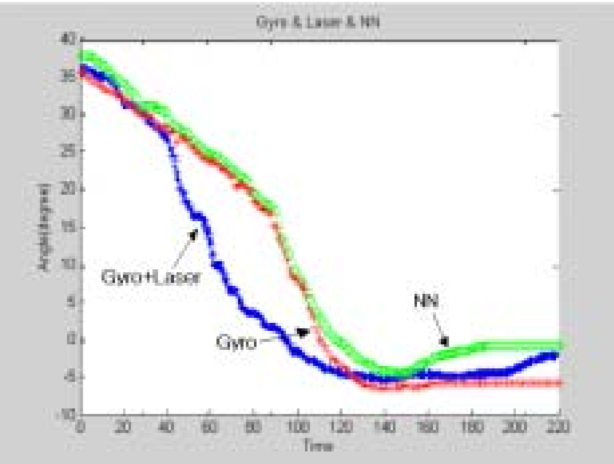

Fig. 17 Heading angle results compared with control laws (slip condition)

6. CONCLUSIONS

In this paper, we performed position tracking experiments with a mobile robot. For localization of the robot, we investigated individually effects of using diverse sensor information. Position estimation due to encoder values makes it fast and easy to know the position of robot at real time but decrease tracking performance because of cumulative errors. To compensate these errors, we used the laser finder which could read absolute position values. We compared and analyzed performances of several kinds of control algorithms. When we use neural network with a cascaded control method, tracking performance of mobile robot is superior.

We found that the RCT control method of neural network had an advantage of externally compensating to existing controllers without modification. For the mobile robot, a laser sensor gave coordinate information of the robot by wireless transmission at a distance. In this way, totally disconnected two systems form a closed loop controlled system.

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