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Parameter Estimation Experiment and Development of Decentralized Caster Modules

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Abstract: Parameter estimation method for distributed active caster has been investigated in this paper. By installing multiple active casters to a target object directly, it becomes a mobile system for transportation and can be moved to the goal position automatically. When the system is used to move an object of irregular shape, the position of each caster module should be estimated because it is basic parameter for control. Therefore, a parameter estimation method based on the kinematic model of each caster module and Kalman filter was proposed. The proposed algorithm has been demonstrated by computer simulation and experimental work.

Keywords: Active Caster, Parameter Estimation, Distribute Modular System, Mobile Robot.

1 INTRODUCTION

Object transportation is a well-known application of mobile robot technology. The representative example, AGV(Automatic Guided Vehicles), has been utilized for factory automation in industrial site. It has been used in various factories because of its capability to move a heavy load and autonomous operation. However, a typical AGV has limitation on load capacity owing to its platform size, and sometimes requires special modification for transporting objects with irregular shape. To cope with this problem, a novel device 'active caster system' has been proposed in previous researches [1, 2]. It is a system consists of multiple mobile caster modules that are independent but collaborate with each other. After installing them directly to a target object to move, and operating them by wireless communication, we can move it to the goal position automatically.

While using the active caster system, the actual problem is that the parameters in the kinematic model of the whole system changes according to the shape of the target object and the attachment of multiple casters. It is required to know the attached position of caster modules for collaboration between them. Therefore, the purpose of this research is to propose a method to estimate the attachment position of each caster module for real application. For that, parameter estimation algorithm based on the kinematic model of each caster module and external sensor information was proposed and demonstrated through computer simulation and experiment. Besides, the method of augmented Kalman filter [3] was also applied. The kinematic model of the mobile system with multiple casters is based on the previous researches [2, 4].

2 KINEMATIC MODEL

Double wheel typed caster was adopted for the caster module as shown in Fig. 1. It has two active wheels that rotate independently, which are connected to both ends of an axle that is also connected to the passive joint by a link. So the system configuration with multiple caster modules can be represented as Fig. 1.

Kinematic model between the velocity of the target object and the angular velocities of three joints, a passive joint and two active wheels, are given as follows. Let $\underline{\dot{X}} = (\dot{x} \quad \dot{y} \quad \dot{\Phi})^T$ be the velocity vector of target object. And $\underline{\dot{\phi}}_i = (\dot{\theta}_{iL} \quad \dot{\theta}_{iR} \quad \dot{\varphi}_i)^T$ denotes the angular velocity vector of joints in the caster module.

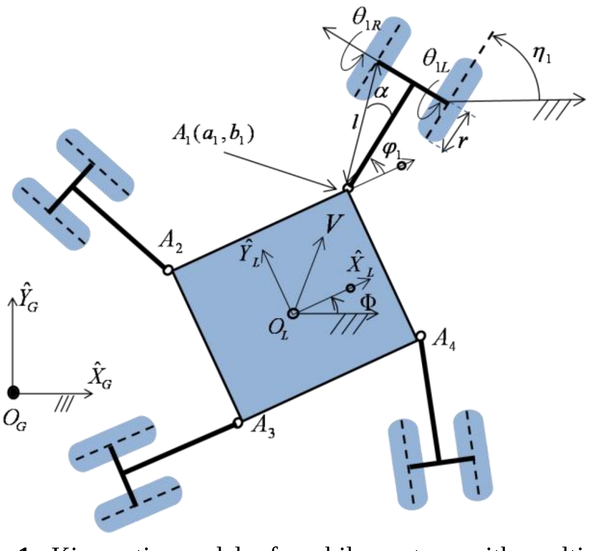

Fig.1. Kinematic model of mobile system with multiple double-wheel-typed casters

The kinematic relationship between $\underline{\dot{X}}$ and $\underline{\dot{\phi}}_i$ is given as

$$\underline{\dot{\phi}}_i = J_i^{-1}\underline{\dot{X}} \quad (1)$$

Where J_i^{-1} denotes the inverse Jacobian matrix of *i*-th caster module, and it can be defined as [2]

$$J_i^{-1} = \frac{1}{lrC_\alpha}\begin{pmatrix} lC_{\varphi_i-\alpha} & lS_{\varphi_i-\alpha} & a_i lS_{\varphi_i-\alpha} - b_i lC_{\varphi_i-\alpha} \\ lC_{\varphi_i+\alpha} & lS_{\varphi_i+\alpha} & a_i lS_{\varphi_i+\alpha} - b_i lC_{\varphi_i+\alpha} \\ rS_{\varphi_i} & -rC_{\varphi_i} & -lrC_\alpha - b_i rS_{\varphi_i} - a_i rC_{\varphi_i} \end{pmatrix}. \quad (2)$$

Where a_i and b_i denote the *x* and *y* position of each caster with respect to the moving coordinate on the object. From Eq. (2), it is found that the kinematic relationship is dependent to the attachment position of each caster module.

3 PARAMETER ESTIMATION ALGORITHM

In this section, a parameter estimation algorithm based on the kinematic model is described. The basic idea is to estimate the kinematic parameters based on the difference between the position information from the external sensor and odometry. The error of odometry is mainly depend on the parameters included in the kinematic relationship. So, they can be estimated with the comparison of motion trajectories measured by external sensor. Here, it is assumed that the dimension of each caster module is sufficiently accurate, and the slippage between the wheel and the ground is small to be ignored.

The state vector including the posture of the object at time *k* is defined as

$$x_k = (x(k) \quad y(k) \quad \Phi(k))^T \quad (3)$$

The state value at time *k+1* is computed with the manner of odometry as

$$x_{k+1} = x_k + \underline{V}_k \Delta t \quad (4)$$

Where $\underline{V}_k$, the velocity of object, is calculated by Eq. (1) with the angular velocity measured by encoders, which is based on the kinematic relationship of each caster as shown in Eq. (2). The actual position of caster module is defined as a_i and b_i. And its initial position is also represented as a_i^* and b_i^*, respectively as follows.

$$a_i = \delta_{a_i} a_i^*, \quad (5)$$

$$b_i = \delta_{b_i} b_i^*. \quad (6)$$

By changing the parameter δ_a and δ_b, the estimation of real position of each caster module is performed. For parameter estimation, the state vector including δ_a and δ_b is defined as Eq. (7).

$$\hat{x}(k|k) = (x(k) \quad y(k) \quad \Phi(k) \quad \delta_a \quad \delta_b)^T \quad (7)$$

Then, Kalman filter was adopted for parameter estimation as follows[3].

$$P(k+1|k) = F_k P(k|k) F_k^T + Q_k \quad (8)$$

$$K_{k+1} = P(k+1|k) H_{k+1}^T [H_{k+1} P(k+1|k) H_{k+1}^T + R_{k+1}]^{-1} \quad (9)$$

$$\hat{x}(k+1|k+1) = \hat{x}(k+1|k) + K_{k+1}[z_{k+1} - H_{k+1}\hat{x}(k+1|k)] \quad (10)$$

$$P(k+1|k+1) = [I - K_{k+1} H_{k+1}] P(k+1|k) \quad (11)$$

Eq. (8) is state prediction covariance. Kalman gain shown in Eq. (9) is utilized for revising the error by using difference between observation value and prediction value [5]. Then, the state value and the covariance are updated by Eq. (10) and Eq. (11) with Kalman gain, respectively.

Now, the new linearized system matrix, F_{aug} and Gaussian process noise with covariance matrix Q_{aug} takes form Eq. (12). The matrix A is the transition matrix linking the augmented states to the location estimate. The matrix S is a fictitious noise injection on the augmented states to ensure convergence.

$$F_{aug} = \begin{bmatrix} F & A \\ 0 & I \end{bmatrix}, \quad Q_{aug} = \begin{bmatrix} Q & 0 \\ 0 & S \end{bmatrix}. \quad (12)$$

Where,

$$A = \begin{bmatrix} \frac{\partial X_k}{\partial \delta_a} & \frac{\partial X_k}{\partial \delta_b} \\ \frac{\partial Y_k}{\partial \delta_a} & \frac{\partial X_k}{\partial \delta_b} \\ \frac{\partial \Phi_k}{\partial \delta_a} & \frac{\partial X_k}{\partial \delta_b} \end{bmatrix}, \quad S = \begin{bmatrix} s_{11} & 0 \\ 0 & s_{22} \end{bmatrix}. \quad (13)$$

4 COMPUTER SIMULATION

Computer simulation has been performed to verify the performance of the proposed method to optimize the target parameters. Fig. 2 shows motion trajectory of the object adopted in the simulation. It was assumed that while the system, i.e. object with the caster module, is moving along trajectory of dotted line, its position can be observed by external sensor such as a camera installed at the ceiling. At the same time, the position is also computed by odometry with the measured angular velocity of joint and wheels. Because of the difference of parameters, there exists position error between them. Finally, this position error is modified by Kalman filter. Fig. 3 shows the change of the estimated parameters. According to the movement of the system, the parameters a_i^* and b_i^* were changed and approached $\delta_a = 0.3$ and $\delta_b = 0.4$, resultantly.

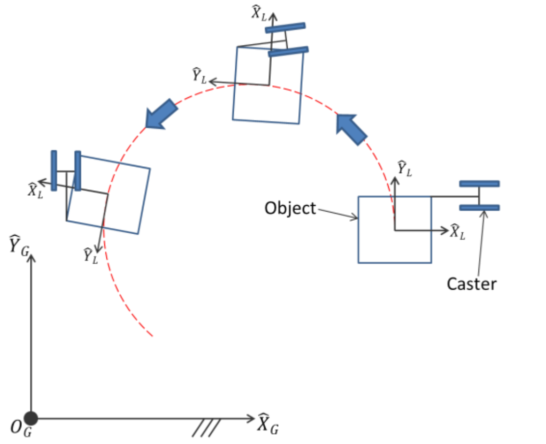

Fig.2. Motion trajectory of the system in simulation

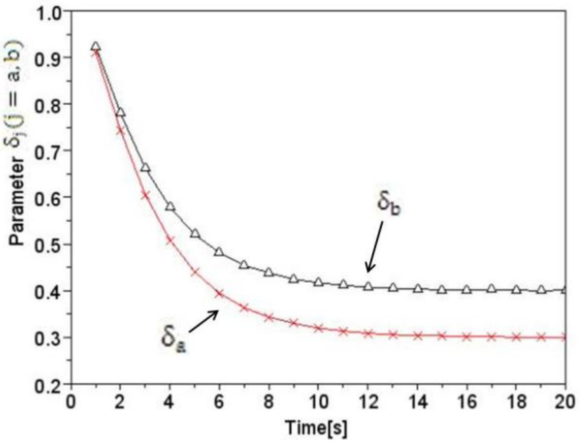

Fig.3. Estimated results of parameters δ_a and δ_b

5 EXPERIMENTS

5.1 Development of experimental caster module

Experimental works were carried out to check the proposed algorithm with real system. For that, a caster module has been manufactured as shown in Fig. 4, which has no actuator at each joint but three encoders to measure angular velocity of each joints. So the system moves manually by human operation.

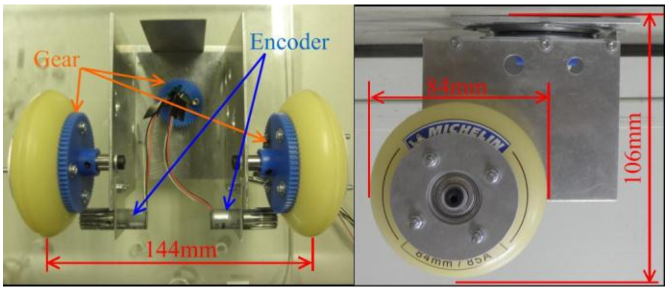

Fig.4. Caster module developed for experiment

5.2 Configuration of experimental system

The configuration of the experimental system and its photograph are shown in Fig. 5 and Fig. 6, respectively. A microcomputer and encoders were used to measure the angular position of passive joint and the angular velocity of both wheels. They can be embodied in a caster module with motors and wireless unit in actual system. In this experiment, the information of each encoder is transferred to the laptop computer for computing odometry. Laser scanner (LRF) is employed as an external sensor to achieve the system position, which is connected to laptop computer through Local Area Network (LAN) communication. In order to achieve the position information by external sensor, scan data from LRF is computed by using Iterative Closest Point (ICP) algorithm. The parameter estimation is carried out in the laptop computer by the algorithm of the previous section with the measured data from LRF and odometry.

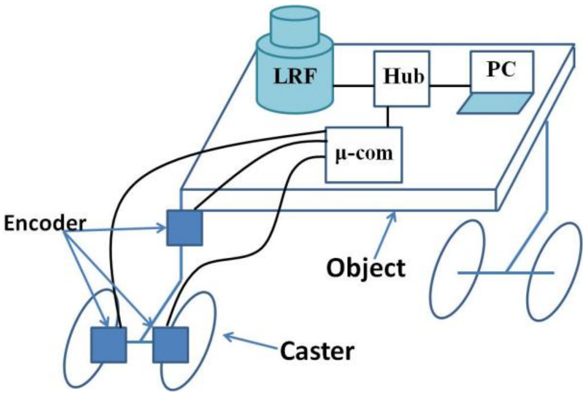

Fig.5. Configuration of the experimental system

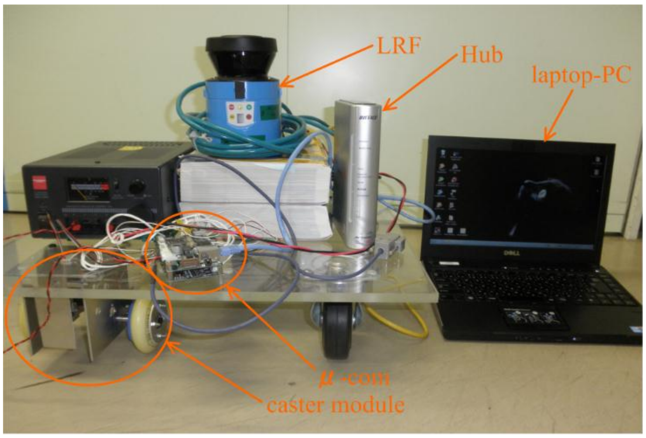

Fig. 6. Photograph of the experimental system

5.3 Experimental result

In the experiment, the position of active caster was estimated while the system is moved by human manual operation. The initial value of parameter and the true value are defined as imaginary caster position and real caster position as shown in Fig. 7, respectively. The motion trajectory of object center in Fig. 7 is measured by LRF in this experiment. As shown in Fig. 8, the motion trajectory of object center was a semi-circular route in this experiment. Fig. 9 shows the resultant change of parameters which were obtained by the proposed algorithm with the measured data. It was observed that the parameters approach to the real value in company with the motion of system resultantly.

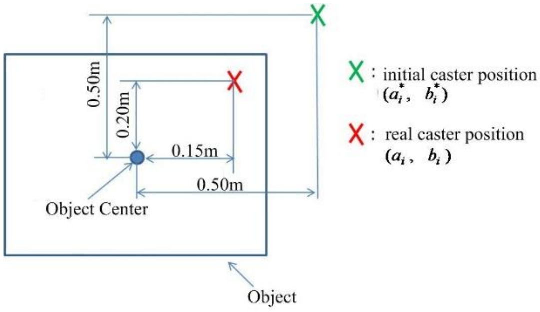

Fig.7. Parameter setting for experiment

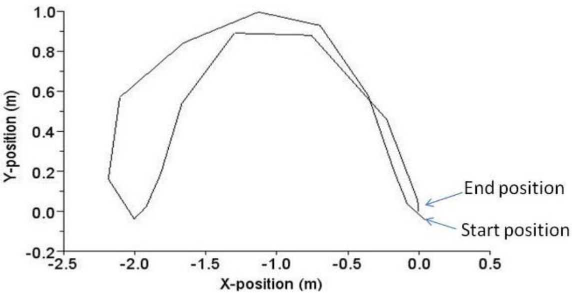

Fig.8. Motion trajectory of the object in experiment

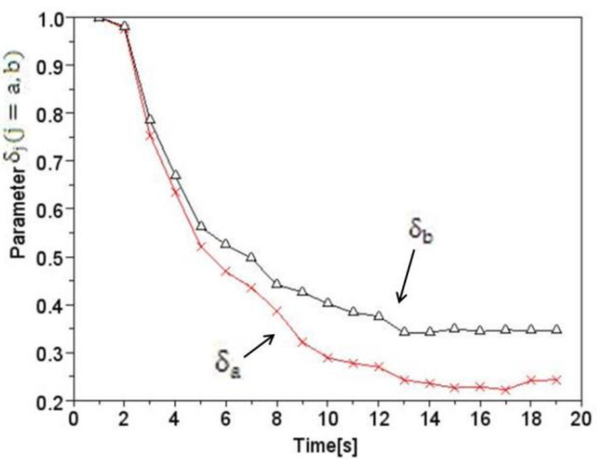

Fig.9. Experimental result on parameters δ_a and δ_b

In order to check the influence of the parameters, both odometry data for the same motion with the estimated value and un-estimated were compared. Fig. 10 shows odometry data of motion trajectories with un-estimated parameters. Fig. 11 shows odometry with estimated parameters, respectively. It is observed that the odometry with estimated parameters shows smaller error that the other. Therefore, the usefulness of the proposed method was confirmed through the experiment.

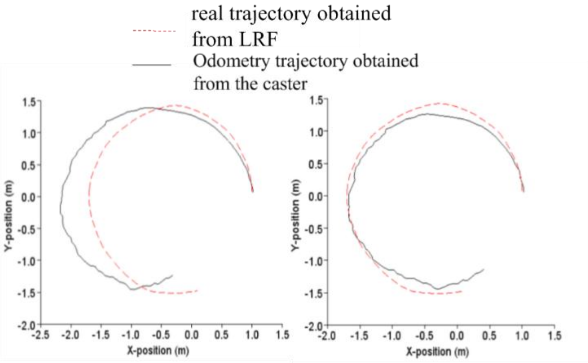

Fig. 10. Motion trajectory by odometry with un-estimated parameters

Fig. 11. Motion trajectory by odometry with estimated parameters

6 CONCLUSION

For real utilization of active caster system, the intelligent method to estimate parameters during its random motion was investigated through computer simulation and experimental works. For real application, redesign of the system with actuators and development of the controller based on wireless communication are now in progress.

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