Implementation of Localization System using Learning Automata based Sensor Fusion in Unmanned Forklifts

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Abstract  
Unmanned forklifts have great potential to enhance the productivity of material handling in dangerous applications because these forklifts can pick up and deliver loads without an operator or any fixed guide. There are, however, many technical difficulties involved in developing unmanned forklifts including localization, map building, sensor fusion, and control. Recently, the NAV200 positioning system has been used as a localization system, which is the most important component of unmanned forklifts. The NAV200 is a laser measurement system for indoor localization with high accuracy and high precision; however, it has some problems in that it may not operate well when it is required to move fast or has to change its direction at an instant. In order to solve these problems, this paper proposes a learning automata based sensor fusion algorithm with dead reckoning using the kinematics of the unmanned forklift and Kalman filter based prediction using the tendency of movement. To demonstrate the feasibility of the suggested sensor fusion algorithm, its performance is evaluated in computer simulations for various cases.

Key Words: Unmanned forklift, Localization system, Sensor fusion, Dead reckoning, Kalman filter, Learning automata

INTRODUCTION  
Forklifts and transporting vehicles that load and transport raw materials and products from racks in industrial sites and warehouses are important elements in the logistics system. However, dangerous working environments where people cannot operate forklifts, such as industrial disasters or sites with radioactive waste, are rapidly increasing.[1] As a method to reduce exposure to hazardous working environments and to reduce industrial accidents, studies on unmanned forklifts or transportation vehicles are actively being carried out.[2],[3] For example, unmanned pallet trucks load pallets as directed by an external operator and automatically move along directed pathways following a paint strip or a guide wire embedded in the ground.[4] Also, unmanned forklifts that can automatically load pallets have been developed and applied to industrial sites due to advancements in unmanned driving, vision, and localization system technologies.[5]–[7] In order to automatically operate an unmanned forklift, various technologies are required. First, technology to recognize the position or location of the forklift is necessary. Especially, forklifts are used in both indoor and outdoor environments, so a localization system suitable for indoor environments is required. Second, since unmanned forklifts have to perform tasks and move to a specific location according to human commands, actuator control technology to move the forklift is necessary. Third, vision technology to allow unmanned forklifts to recognize coordinates for pallet loading is needed. Fourth, map building and path planning technologies for the forklift to move to a specific location are necessary. Fifth, technology to recognize and evade obstacles that may be encountered during movement along a set path by the forklift is required. Lastly, measurement technology that utilizes sensors is needed to recognize obstacles and to measure the height of the fork of the forklift. In the future, technology to distribute tasks to multiple forklifts moving together will be required as well. Among the various unmanned forklift technologies, numerous studies on localization systems are being conducted. The standard method for localization, developed by Rezeai and other researchers, is the utilization of GPS or DGPS,[8],[9] However, the use of GPS or DGPS is problematic in indoor environments, and as such is rarely used indoors. As a result, methods are being studied using wireless LAN, PIR sensors, ultrasound, and lasers for localization in indoor environments.[10]–[13] However, all methods have advantages of their own, along with disadvantages, and so there were a number of difficulties in performing accurate localization indoors. For this reason, localization methods through sensor fusion have been proposed.[14]–[16] In particular, one method using the laser based NAV 200 has been proposed.[1],[2] The laser based NAV 200, previously described in the literature, is able to recognize the location of an unmanned forklift within a few mm, and so it has been used in many commercial AGVs. However, NAV 200 has a measurement period of approximately 135ms, making it difficult to use for accurate localization when the unmanned
forklift is driving or turning at high speeds.[17] During high speed turns, the NAV 200 either outputs no data due to measurement errors or gives erroneous data for a certain period of time.

In this study, in order to resolve the issues with NAV 200 so that high speed driving is possible for unmanned forklifts, the sensor fusion method is proposed. First, Kalman prediction was applied to the NAV 200 localization data output to partially remove uncertainties. Along with this, additional localization data were obtained using the dead reckoning method with the encoder and steering angle sensor installed on the unmanned forklift.[18],[19] Lastly, using learning automata, the unmanned forklift localization method was used to produce location data from two sets of location data.[20]

UNMANNED FORKLIFT LOCATION DATA ACQUISITION SYSTEM

Unmanned Forklift Overview

Figure 1 shows an unmanned forklift using the CRX-10 model upright electric forklift manufactured by CLARK. The unmanned forklift in the figure was developed by applying the CAN(Controller Area Network) network based distributed control system. The distributed control system of the unmanned forklift was developed so that the corresponding function of each independently operating module required for unmanned operation can be performed using the various data transferred through the network.[1]

The network based distributed control system of the unmanned forklift is composed of six modules. The distributed control system of the unmanned forklift is composed of the main control module that manages the entire system, traction and steer control modules related to forklift driving, fork and pallet detection modules for pallet loading, and an obstacle detection module.

The sensor fusion system that resolves the issues of the NAV 200 for the unmanned forklift is located in the main control module; the structure is shown in Figure 2. In the figure, the location data for the unmanned forklift are created using dead reckoning and Kalman prediction. Dead reckoning is a localization prediction method that calculates the location by obtaining the direction and travel distance of the unmanned forklift using the steering angle sensor and encoder installed in the moving platform.[18] Compared to the NAV 200, this localization method using dead reckoning has short measurement periods for the distance and direction sensors. On the other hand, the Kalman prediction repeats the estimation and compensation steps, which minimize the measurement error, making this an effective estimation method for a model that includes the noise component of the measurement device. This localization method using Kalman prediction has the advantage that estimated values can be used instead when location data are not outputted or when erroneous data are produced at certain times by the NAV 200.

Location Data Obtained Using Dead Reckoning

In this study, for the kinematic structure of the unmanned forklift shown in Figure 3, the steering wheel angle($S_o$) was used to measure the rotation radius($R_o$), the encoder was used to measure the travel distance, and the location data were obtained through dead reckoning. The current location of the unmanned forklift can be expressed as Eq. (1).

$$X_d(k) = [x_d(k), y_d(k), \theta_d(k)]$$  (1)
Here, \( x_d(k), y_d(k) \) and \( \theta_d(k) \) refer to the location data of the unmanned forklift; the data calculated using dead reckoning can be expressed as Eq. (2).

\[
X_d(k+1) = [x_d(k+1), y_d(k+1), \theta_d(k+1)]
\]  
(2)

To obtain the location data of the unmanned forklift, the rotation radius can be expressed as Eq. (3).

\[
R_f = D_f \times sec(90° - \theta_f)
\]  
(3)

Here, \( D_f \) is the distance between the front and rear axles. The travel distance of the unmanned forklift for a very short period of time can be expressed as Eq. (4).

\[
\sqrt{(R_f \sin \theta_f)^2 + (R_f(1 - \cos \theta_f))^2} = R_f \sqrt{2(1 - \cos \theta_f)}
\]  
(4)

Here, \( \theta_f \) is the angular change. The process of obtaining the next location of the unmanned forklift using the calculated travel distance and dead reckoning can be expressed as Eq. (5).

\[
X_d(k+1) = X_d(k) + R_f \sqrt{2(1 - \cos \theta_f)} \times \begin{bmatrix} \cos \theta_f \\ \sin \theta_f \end{bmatrix}^T
\]  
(5)

**Figure 3:** Kinematics analysis of unmanned forklift

**Location Data Obtained Using Kalman Prediction**

Based on a mathematical model, the Kalman filter repeats the processes of estimation and compensation to minimize the measurement error covariance, and so this method is able to remove the uncertainty caused by the NAV 200.[22] In this study, the discrete system model, which has an equation of state and an observation equation that estimate the location of the unmanned forklift, can be expressed as Eq. (6).

\[
X_k(k) = AX_k(k-1) + Bu(k-1) + w(k-1)
\]

\[z(k) = HX_k(k) + v(k)
\]  
(6)

Here, \( X_k(k) = [x_k(k), y_k(k), \theta_k(k)]^T \) is the equation of state vector representing the location of the unmanned forklift. \( z(k) \) is the observation equation observation vector, \( w(k) \) is the system noise, and \( v(k) \) is the observation noise. Also, the noise vectors \( w(k) \) and \( v(k) \) do not have any correlation with each other; these vectors have Gaussian distributions and are assumed to have covariance values as shown in Eq. (7).  

\[
E[w(k)] = E[v(k)] = 0
\]

\[
cov[w(j), w(k)] = E[w(j)w(k)^T] = Q(k)
\]  
(7)

\[
cov[v(j), v(k)] = E[v(j)v(k)^T] = R(k)
\]

\[
cov[w(j), v(k)] = E[w(j)v(k)^T] = 0
\]

In order to model the estimation and compensation steps of the Kalman filter, the initial estimation value is \( X_0(k) \), and post estimation value is \( X_k(k) \); using this, the initial estimation error \( e_0(k) \) and the post estimation error \( e(k) \) can be expressed as Eq. (8).

\[
e_0(k) = X_0(k) - X_k(k)
\]

\[
e(k) = X_k(k) - X_k(k)
\]  
(8)

According to the orthogonality principle, which says the linear vector space composed of the estimation values is orthogonal, for the estimation error regarding the optimal linear estimation value, the initial estimation value error covariance \( P_0(k) \) and the post estimation value error covariance \( P(k) \) of the current and compensated state vectors can be expressed as Eq. (9).

\[
P_0(k) = E[e_0(k)e_0^T(k)] = E[(X_0(k) - X_k(k))(X_0(k) - X_k(k))^T]
\]

\[
P(k) = E[e(k)e^T(k)] = E[(X_k(k) - X_k(k))(X_k(k) - X_k(k))^T]
\]  
(9)

The Kalman prediction estimates the location by using the initial estimation value in the step, expressing the differences between the post estimation value \( X_k(k) \) estimated in the previous step and the measurement estimation value \( H(k) \), \( X_k(k) \). In other words, as can be observed in Eq. (10), the error of the initial estimation value \( X_k(k) \) was calculated for the measurement value \( z(k) \) to update the post estimation value \( \tilde{x}_k(k) \); then, the step of multiplying the gain value followed by adding the optimum evaluation value is repeated.

\[
\tilde{x}_k(k) = X_k(k) + K(k) (z(k) - HX_k(k))
\]

\[
X_k(k) = A(k-1)\tilde{x}_k(k-1)
\]  
(10)

Here, \( K(k) \) is the Kalman gain value, which is repeatedly calculated and updated through recursive arithmetic. Also, \( (z(k) - HX_k(k)) \) is the value arithmetically obtained from the actual output value measured by the measurement device and the initial estimation value error.
In order to calculate the Kalman gain value, Eq. (11) can be obtained by substituting Eq. (9) into Eq. (10).

\[
P(k) = P_-(k) - K(k)HP_-(k) = P_-(k)K(k)^T H^T + R(k)K(k)^T
\]

Differentiation of Eq. (11) to obtain the optimum value of the Kalman gain using the matrix differential equations results in Eq. (12).

\[
K(k) = \frac{P_-(k)H^T}{H P_-(k)H^T + R(k)}
\]

Substituting Eq. (12), which calculates the Kalman gain value, into Eq. (11) gives the covariance matrix expressed as Eq. (13).

\[
P(k) = P_-(k) - K(k)HP_-(k)H^T + R(k)\gamma I
\]

The covariance matrix value is used to estimate the (k+1)-th cycle value; the next cycle estimation value can be expressed as Eq. (14).

\[
X_{k+1} = AX_k + Bu(k)
\]

Substitution of the covariance matrix Eq. (14) into Eq. (13) allows the estimation of the previous value of the covariance matrix, as shown in Eq. (15). Using this method, the steps of location variation estimation data value calculation and compensation are repeated for the unmanned forklift.

\[
P_{-}(k) = A(P_{-}(k) - K(k)HP_{-}(k))A^T + Q(k)
\]

Hence, in the Kalman prediction, the initial estimation value \(X_{i}(k+1)\) used in the update process of the error covariance \(P(k)\) is outputted as the coordinates of \(X_{i}(k+1)\).

**Sensor Fusion using Learning Automata**

Generally, the learning automata is composed of the selectable behavior set and the probabilities of selecting each behavior. The probability for each behavior is continuously adjusted by the enhancement algorithm according to the reaction of the environment interacting with the learning automata when that behavior is selected.[19] For example, among the coordinates obtained from dead reckoning and the Kalman prediction, when it is determined that the error is small for the coordinates selected and applied for the unmanned forklift according to the highest probability for the dead reckoning coordinates, the enhancement algorithm increases the probability of the coordinates selected using dead reckoning before selecting the next coordinates, while decreasing the probability of selecting the coordinates obtained using the Kalman prediction. In the process of repeating these steps, the probability of selecting the coordinates with the smallest error gradually increases and the probability of selecting coordinates with increasing error decreases, so that the problem of the NAV 200 system of difficulty of accurate localization for high speed turns can be effectively resolved.

Figure 4 shows the sensor fusion algorithm using the learning automata to determine the location of the unmanned forklift. In the figure, it can be observed that the location coordinates of the NAV 200 are obtained after initializing the unmanned forklift. After obtaining the location coordinates of the NAV 200, the coordinates are calculated using the Kalman prediction method explained in Section 2.3; the steering angle sensor and encoder explained in Section 2.2 are used to calculate the coordinates using dead reckoning. Next, Eq. (16) is used to calculate the ISE (Integral of the square of error) of the location coordinates calculated using dead reckoning and Kalman prediction.[23]

\[
ISE_d(k) = \sum_{k=1}^{n} \Delta t \cdot e_d^2(k)
\]

\[
e_d^2(k) = (x_m(k) - x_d(k))^2 + (y_m(k) - y_d(k))^2
\]

\[
ISE_k(k) = \sum_{k=1}^{n} \Delta t \cdot e_k^2(k)
\]

\[
e_k^2(k) = (x_m(k) - x_k(k))^2 + (y_m(k) - y_k(k))^2
\]

Here, \(\Delta t\) is the time domain and \(e(k)\) is the difference between the location coordinates calculated through dead reckoning and Kalman prediction using the location data measured by NAV 200. \(x_m(k)\) and \(y_m(k)\) are the location coordinates measured by NAV 200; \(x_d(k)\) and \(y_d(k)\) are the location coordinates calculated through dead reckoning; and \(x_k(k)\) and \(y_k(k)\) are the location coordinates calculated through the Kalman prediction. Eq. (17) is used to calculate \(LA_d(k+1)\) after calculating \(ISE_d(k)\) and \(ISE_k(k)\).

\[
LA_d(k+1) = LA_d(k) + \alpha(\frac{ISE_k(k)}{ISE_d(k) + ISE_k(k)})
\]

Here, \(\alpha\) is a variable used to prevent the rapid variation of the final location coordinates as the \(LA_d(k+1)\) value suddenly changes according to the error of the location coordinates measured and calculated through dead reckoning. In this study, \(\alpha = 0.1\) was selected because fusion coordinates with a sampling time of 13.5ms are produced 10 times faster than the measurement period of 135ms of the NAV 200.

After calculating \(LA_d(k+1)\), the \(LA_d(k+1)\) value is compared with \((ISE_k(k)/ISE_d(k) + ISE_k(k))\) to calculate the \(LA_d(k+1)\) value if \(LA_d(k+1)\) is bigger. On the other hand, if the \(LA_d(k+1)\) value is smaller, the case when the \(LA_d(k+1)\) value rapidly changes is determined and the \(LA_d(k+1)\) value is recalculated using Eq. (18).

\[
LA_d^*(k+1) = \frac{ISE_k(k)}{ISE_d(k) + ISE_k(k)}
\]

After calculating the values of \(LA_d(k+1)\) and \(LA_d(k+1)\), the sensor fusion location coordinates using the learning automata are calculated using Eq. (19).
\[
\begin{align*}
\hat{x}_{\text{fusion}}(k) &= LA(k) x_d(k) + (1 - LA(k)) x_k(k) \\
\hat{y}_{\text{fusion}}(k) &= LA(k) y_d(k) + (1 - LA(k)) y_k(k)
\end{align*}
\]  

(19)

Figure 4: Structure of the sensor fusion algorithm using learning automata

Performance Evaluation of the Unmanned Forklift Localization System using the Learning Automata

The performance evaluation of the unmanned forklift localization system using the learning automata was carried out by collecting the location data of the unmanned forklift manufactured using the CLARK CRX-10 model. The steering angle and steering speed for dead reckoning were measured using variable resistors installed in the main wheel; the encoder value was measured using the timer and counter of the module using AT90CAN128 MCU. The location data for the Kalman prediction was measured using RS-232 communication for the NAV 200 location data. Here, the NAV 200 location data measurement period was configured to 135ms and the calculation periods for dead reckoning and Kalman prediction were set at 5ms and 13.5ms, respectively. The learning automata calculation period was set at 10ms and a MATLAB code was prepared to use the most recent value depending on the calculation period. For the experiment, each set of data were collected and the collected data were used to show that accurate and short period collection of location data is possible by applying the sensor fusion method using the proposed learning automata.

Figure 5(a) shows the case in which the location data obtained according to dead reckoning are not accurate due to problems of precision stemming from main wheel slip or modeling of the unmanned forklift. Meanwhile, the location data obtained using the Kalman prediction shown in Figure 5(b) were found to be relatively acceptable. Figure 5(c) shows the results of using the learning automata sensor fusion and the location data from Figures 5(a) and 5(b). The sensor fusion result, determined with the relatively well-obtained location data of two types, was found to be outstandingly good. Also, it was found that the sensor fusion result for the case in which one set of location data had relatively significant error was well outputted by placing high weight on the relatively excellent Kalman prediction data. As can be seen in Figure 5(d), the ISE performance index also showed that the sensor fusion results had relatively superior values. Especially, while the ISE value of the Kalman prediction was 457.86, the ISE value of the sensor fusion method using the learning automata was lower, at 412.99. This suggests that the location data obtained using the sensor fusion method were more accurate than the Kalman prediction location data.

Figure 6(b) shows the case in which the Kalman prediction location data diverge due to NAV 200 location data error caused by rapid turning of the unmanned forklift. In contrast, the dead reckoning location data result shown in Figure 6(a) was relatively acceptable. Figure 6(c) shows the learning automata sensor fusion results obtained using the location data in Figures 6(a) and 6(b). Even with error of the NAV 200 location data, the sensor fusion results were relatively excellent. Similarly, the sensor fusions results for the ISE performance index, as shown in Figure 6(d), were also relatively excellent. While the ISE value of dead reckoning was 456.62, the ISE value of the sensor fusion method using the learning automata was lower, at 333.56. Similar to the earlier case, the sensor fusion method location data were more accurate than the dead reckoning location data.

Figure 7(b) shows the case in which the rapid turning of the unmanned forklift resulted in no NAV 200 location data output, so that there was no Kalman prediction location data estimation. Hence, this is a case in which there is no NAV 200 location data. On the other hand, the location data obtained using dead reckoning, shown in Figure 7(a), reveal relatively satisfactory results. Figure 7(c) shows the learning automata sensor fusion results obtained using the location data from Figures 7(a) and 7(b). Even without the NAV 200 location data, the sensor fusion results obtained using the dead reckoning location data were relatively well outputted. As shown in Figure 7(d), the sensor fusion results were also found to be relatively excellent for the ISE performance index. While the ISE value of dead reckoning was 206.66, the ISE value of the learning automata sensor fusion method was lower, at 196.65.

As can be observed in the experiment results, the sensor fusion method using the learning automata proposed in this study was found to be able to supplement the problems of the conventional system, which provides the location data of the unmanned forklift. In particular, except for cases in which the location data are not outputted for a long period of time, considerably outstanding location data can be produced over short periods.
CONCLUSION

In this study, in order to resolve the problems of the NAV 200 method so that high speed driving is possible for an unmanned forklift, the sensor fusion method was proposed. Location data were obtained using dead reckoning and Kalman prediction for the NAV 200 location data output. Using the obtained data, a method of producing location data for the unmanned forklift from two sets of location data using the learning automata was proposed. Lastly, the performance of the sensor fusion method using real unmanned forklift location data was evaluated to verify the potential usability. The following conclusions were obtained.

First, it was found experimentally that existing localization systems, such as the NAV 200 system, which provides location data for the unmanned forklift, frequently experience the provision of erroneous location data or a lack of data during high speed turns. Especially, the existing localization system has relatively slow production of location data output periods, leading to limitations in the high speed location control.

Second, using the sensor fusion method and employing the learning automata presented in this study, it was found that relatively accurate location data could be provided even when the location data from the NAV 200 were incorrect or when location data were not being produced. Compared to the existing location data system, the proposed method had a data output period that was 10 times faster, showing that accurate location control was possible.
REFERENCES


