LOCALIZATION BASED ON MATCHING LOCATION OF AGV

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ABSTRACT

Localization is a critical issue in mobile vehicles. Mobile vehicles must know its position and orientation in order to movement to reach the goals precisely. In this paper, we describe localization techniques for AGV that is based on the principle of Kalman Filtering (KF) algorithm estimation. This paper addresses the problems of factory navigation and modelling with focus on keeping automatic travelling along the control path of the AGV. AGV path is generated by cubic polynomial trajectory and stored in memory. Position and orientation is measured by using encoder sensor on driving and steering axes. We develop the control and localization system. Reference path and observation measurement are matched. To keep track of the matching result of both positions, the estimated location information used to update the vehicle's position by using the Kalman Filtering (KF) algorithm. The proposed algorithm is verified by simulation using Matlab software and implemented on PLC TSX micro from SCHNEIDER. The implemented program is written by PL7 Pro using Grafcet techniques.

KEYWORDS: Localization, Kalman Filtering (KF), AGV, Trajectory, Control System

1. INTRODUCTION

Position and orientation of vehicle must keep the precise navigation and known its positioning at each place during travelling. To known and maintain its position, the currently the localization is the key of research on mobile vehicle. AGV is one of the significance of the present research trend. In industrial application, manufacturing factory is brought the mobile vehicle to incorporate working with other machine in order to being the automated manufacturing system. Many applications were adopted the AGV in different tasks such as material handling system, AS/RS system, transportation system, etc. Thus the research on the localization of mobile vehicle has increasingly researched in different aspects for improving the ability of vehicle. For reviewing the past research, several methods have been reported the localization of mobile vehicle such as [4-5] was developed a system in which the basic localization algorithm is formalized as a vehicle-tracking problem, employing an extended Kalman filter (EKF) to match beacon observations to a navigation map to maintain an estimate of mobile robot location. Tong and Tang proposed the robot self-localization. They applied the sensor fusion algorithm, which is used ultrasonic and CCD sensors, to filter out unreliable the sensor data reading. Moreover Extend Discrete Kalman Filters (EDKF) used to design for raw sensor data fusion to obtain more reliable representation in environment perception procedures [6]. Modeling of ultrasonic range sensors was developed by [7], and they presented a probabilistic model of ultrasonic range sensors using back propagation neural networks trained on experimental data. Extend Kalman filter is used for update location from the prediction and observation matching as shown in [7-8]. Self-localization techniques by using probabilistic for mobile robot that based on the maximum-likelihood estimation were also done by [9]. For outdoor navigation problem of mobile robot, [10] reported the localization with 2-D mobile robot localization based on observability analysis in order to determine the undergo difficulties. They developed the localization algorithm called multisensor localization system (MLS). Due to nonlinear system model obtained in state-space description, Extend Kalman Filter is applied for estimate the state X which is done in two steps, prediction and filtering, respectively. The use of GPS and inertial plate sensor for outdoor navigation also is presented by [11]. They presented the localization algorithm based on Kalman filtering that tries to fuse information coming from an inexpensive single GPS with inertial data and map-based data. And also [12] developed a localization system that employs two methods. The first method uses odometry, a compass and tile sensor, and global position sensor (GPS). An Extended Kalman filter integrates the sensor data and keeps track of uncertainty associated with it. The second method is based on camera pose estimation. Another localization method was implemented and based on vision sensor. As reported by [13], they proposed a new approach for determining the location of a mobile robot using image of a moving object. This scheme combines data from the observed position, using dead-reckoning sensors, and the estimated position, using images of moving objects captured by a fix camera to determine the location of a mobile robot. The proposed methods utilizes the error between the observed and estimated image coordinates to localize the mobile robot, and the Kalman filtering scheme is used for the estimation of mobile robot location. [14] applied the vision based localization, and used Monte Carlo for extracting each image in the database a set of possible viewpoints using a two-dimension map of the environment, but [15] used vision sensor to localize and build simultaneous three-dimensional map in global localization. Multiple robot formation is done by [16] to localize the group of mobile robots, a leader and follower control.

In this paper a new approach of an AGV is proposed. It is organized as follows. The system architecture is explained. Next section deals with Kalman filter. Furthermore localisation and control system is proposed in this study. The simulation study and experiment of AGV implementation is described, and the conclusion is given in final part.

2. SYSTEM ARCHITECTURE DESCRIPTION

Figure 1 Photo of the AGV prototype

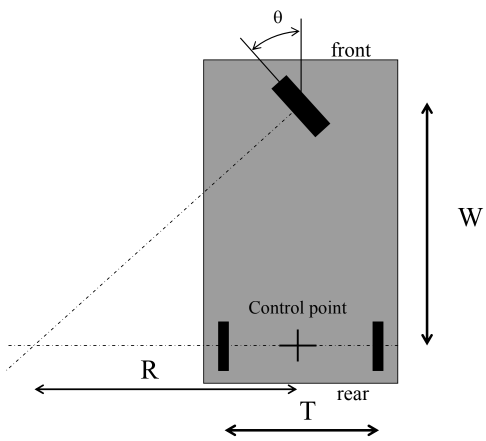

Figure 2 AGV prototype architecture

The AGV prototype design is based on existing JUMBO industrial truck as shown figure 1. It is a three wheels vehicle as shown in figure 2. The front wheel is used for driving and steering the AGV and the two rear wheels are free. The steering and driving are DC motor. Two encoders are individually attached on the two rear wheels in order to measure the vehicle displacement and then calculate its real time position and orientation. The choice of positioning the encoders on the free wheels provides to the vehicle an accurate measurement of its progression. A programmable logic control (PLC) is used for motion control. The parameters of the motion are driving speed and steering angle which determine the evolution of the position and orientation of the AGV. The input and output signal are interfaced with PLC module. The inputs are the encoder signal from left and right rear wheels. The driving speed and steering angle are calculated form these inputs and the digital output is converted to analog signal to drive amplifier of the driving motor and steering motor on front wheel as shown in figure 3.

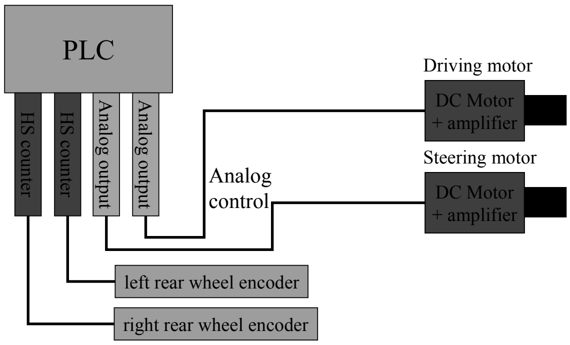

Figure 3 AGV prototype command architecture

3. KALMAN FILTER

Vector Kalman filter [3] is formulated with state equations for linear system as following;

$$
\begin{aligned}
x(k) &= Ax(k-1) + w(k-1) \\
y(k) &= Cx(k) + v(k)
\end{aligned}
\tag{1}
$$

Where $x(k)$ and $x(k-1)$ are state transition matrix by column vector at time k and $k-1$, respectively. $w(k-1)$ is a noise process which is white obtained by-zero mean and independent of all others in dimension of column vector. A is a system transition coefficients with dimension of square matrix. $y(k)$ is the measurement state output matrix at time k. C is the measurement or observation matrix. $v(k)$ represents an additive noise matrix during measurement process at time k.

3.1 Kalman Filter Estimator

Procedure of the Kalman filter estimator can be successfully computed to optimal estimation at each step as following:

Estimator:

$$\hat{x}(k) = A\hat{x}(k-1) + K(k)\left[y(k) - CA\hat{x}(k-1)\right] \tag{2}$$

Filter gain:

$$K(k) = P_1(k)C^T\left[CP_1(k)C^T - R(k)\right]^{-1} \tag{3}$$

Where $P_1(k) = AP(k-1)A^T + Q(k-1)$ (4)

Error covariance matrix:

$$P(k) = P_1(k) - K(k)C(k)P_1(k) \tag{5}$$

The optimum filter deviation of estimation is needed to minimizing the random process system. By estimation, we need the best estimated signal $\hat{x}(k)$ at time k of the estimation signal of $x(k)$. The error of state estimation between two signal vectors at time k needed to minimize to zero by using mean-square error corresponding to

$$p(k) = E\left[e^2(k)\right] \tag{6}$$

Where $e(k) = x(k) - \hat{x}(k)$ is the error.

The problem is how to form $\hat{x}(k)$, the best linear estimate (filter value) of $x(k)$ and how to form $\hat{x}\langle k|k-1\rangle$ is the best predicted value. Mean estimators that minimize the mean-square error of each signal component simultaneously as shown by (7) for filter operation each mean-square error.

$$E\left[x_\alpha(k) - \hat{x}_q(k)\right]^2 \qquad \text{where } \alpha = 1,2\ldots,q \tag{7}$$

The error is to be minimized, and α is a number of signal components.

The observation noise covariance matrix is written as

$$R(k) = E\left[v(k)v^T(k)\right] \tag{8}$$

Similarly, for the signal noise, we have

$$Q(k) = E\left[w(k)w^T(k)\right] \tag{9}$$

Where $Q(k)$ represents the system noise covariance matrix. If there is no noise correlation between noise processes, the off-diagonal terms are zero.

The mean-square error covariance matrix can be obtained by (10).

$$P(k) = \left[e(k)e^T(k)\right] \tag{10}$$

4. LOCALIZATION AND CONTROL SYSTEM

4.1 Localization System

AGV mobile vehicle is needed to move with the precision position and orientation along the defined path. Vehicle must keep the command trajectory generated by path definition. Due to the error sources occurred during moving, then mobility would estimate and adjust position and orientation itself with knowledge of system estimation known as Kalman filter. The localisation technique of AGV has shown in figure 4 as described in block diagram.

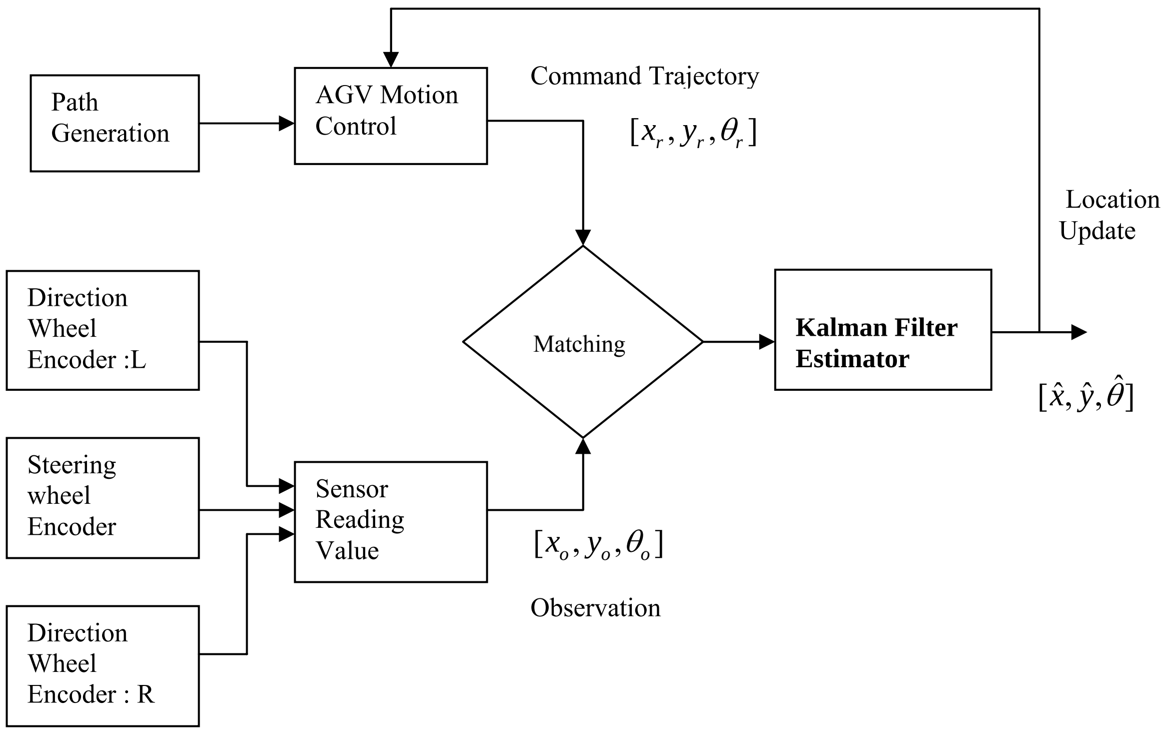

Figure 4 Location estimation of AGV

AGV configuration is defined its position and orientation (x, y, θ).System consider with dynamics of AGV motion can be modelled by (11).

$$\dot{X} = \begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{pmatrix} \cos\theta & 0 \\ \sin\theta & 0 \\ 0 & 1 \end{pmatrix} \bullet \begin{bmatrix} v \\ \omega \end{bmatrix} + w \Leftrightarrow f(X, u, w) \tag{11}$$

Where $u = [v \quad \omega]^T$ are the translational and rotational velocities of AGV, respectively and w is the measurement noise with diagonal matrix component assumed with stationary value [4].

Path generation used for command trajectory of AGV motion is generated for point to point motion by using cubic polynomial trajectory in the form as described by (12)

$$q(t) = a_0 + a_1 t + a_2 t^2 + a_3 t^3 \tag{12}$$

Then the desired velocity is given as

$$\dot{q}(t) = a_1 + 2a_2 t + 3a_3 t^2 \tag{13}$$

We give four constraints with independent coefficients that the trajectory must satisfy.

From block diagram in figure 4, the localization can be done for maintaining the AGV movement along with the given path. Observations are measured by using encoder attached on wheels of AGV in translational and rotational exes. Estimation is performed by Kalman filter, the matching uses for compare the current observer and trajectory command, the error is occurred during this process. The estimation of AGV location will correct and update its positioning by Kalman filter estimator algorithm.

4.2 Control System

The deviation error being evaluated, the steering and driving command signal can be calculated and converted to analog signal by the PLC. The steering and driving control strategy are showed by the to simple block diagram figure 5. The correction applied to the command signal is a proportional one for the driving signal and proportional derivative for the steering signal.

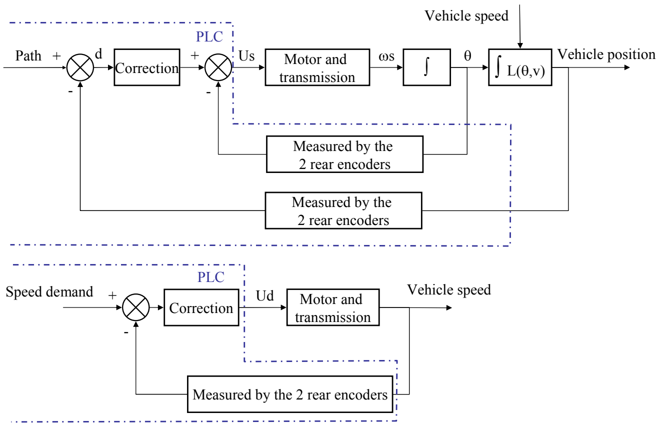

Figure 5 block diagram of steering and driving control

The control algorithm of the AGV has been implemented by using PLC TSX micro form SCHNEIDER. The implemented program is written by PL7 Pro using Grafcet and structured text language. The main inputs of the PLC are high speed up and down counter connected to the 2 encoders. The outputs of steering and driving command are converted to analog output ranged by 0-5 V. The grafcet loop executes 3 consecutive tasks. Control loop is executed every 5 ms.

5. SIMULATION RESULTS

Estimation of AGV position and orientation is performed by using Matlab software. In this study, we develop the simulation model with numeric parameters obtained from experiment test. The initial condition is set the starting point of motion with $[x_s, y_s, \theta_s] = [0,0,0]$ and set the final position in the first segment of controlled path as shown in Appendix A. Repeating the procedure to testing, but incrementally controlled path segment was done.

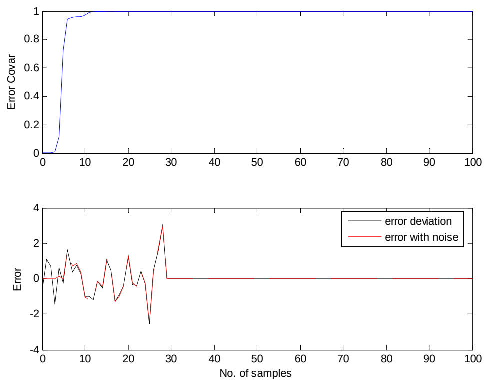

Figure 6 Error of estimation from displacement axis

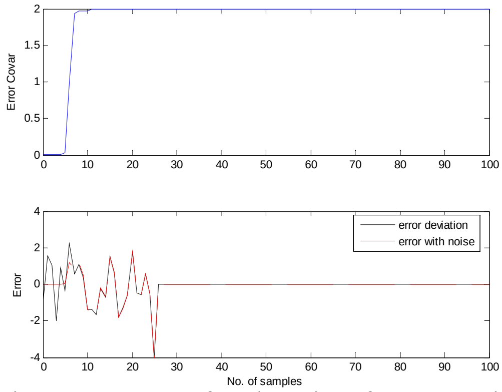

Figure 7 Error of estimation from steering axis

Path is generated to control AGV motion following trajectory specified with point to point command. The state-space model of AGV estimation system by Kalman filter is applied to verifying the AGV pose, and measurement parameters is used for this simulation study. Different axes of controlled position and orientation are separately estimated the AGV pose. Displacement controlled axis is measured with process noise 10^{-3}. R and Q are observation noise covariance and system noise covariance is set to 1 as shown on figure 10. Filter gain (K) of the estimated displacement axis is about 0.8889. Steering controlled axis is measured with process noise 10^{-6}. R and Q are observation noise covariance and system noise covariance is set to 2 as shown on figure 11. Filter gain (K) of the estimated steering axis is about 0.9994. Error of the estimation of true and estimate output value is become to steady state in the final of position specified by red line as shown in figure 6 and figure 7, respectively. Error of the estimation of true and measurement noise output value is become to steady state in the final of position specified by black line as shown in figure 6 and figure 7, respectively.

6. CONCLUSION

This article presents a localization of AGV by Kaman filtering algorithm. Overall structure of designing AGV is described. Control of AGV motion is implemented by using PD control scheme. Displacement axis and steering axis are separated to implement the motion control. In this research, we proposed the localization system for estimation of AGV. Position and orientation are estimated by Kalman filtering in state-space model. Position and orientation of AGV are measured and used for simulation for localization system. Simulation by using Matlab software is used for verifying the estimation positioning of AGV. We conclude that the vehicle can reach from the initial position moved along with generated path by cubic polynomial trajectory to the target position with accurate location. Actual and estimated position outputs are compared and no error in the steady state position of two exes, displacement axis and steering axis with different error covariance value. Actual positions and measurement noise are compared and no error in the steady state position of two exes, displacement axis and steering axis. Finally, Kalman filtering algorithm can be applied for AGV localization system. Future work is planed to increase the accuracy of the system by equip more sensors for observation technique. Treatment of dynamic model of vehicle is also planed to the next step.

7. ACKNOWLEDGMENTS

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8. REFERENCES

[1] S. Butdee and A Suebsomran, Learning and recognition algorithm of intelligent AGV system, *GCMM2006*, 13-72.
[2] S. Butdee, F. Vignat, and A. Suebsomran, Self-alignment control of an automated unguided vehicle, *IDMME06*, 16-19 May 2006.
[3] S.M. Bozic, Digital and Kalman filtering, *Edward Arnold*, (1990)
[4] G.C. Anousaki and K.J. Kyriakopoulos, Simultaneous Localization and map building for mobile robot navigation, *IEEE Robotic and Automation Magazine*, 1999, 42-53
[5] J.J. Leonard and H.F. Durrant-Whyte, Mobile robot localization by tracking geometric beacons, *IEEE Transactions on Robotics and Automation*, Vol.7 (1991) 376-382

[6] K-T. Song and W-H. Tang, Environment perception for a mobile robot using double ultrasonic sensors and a CCD camera, *IEEE Transactions on Industrial Electronics,* Vol. 43 (1996) 372-379

[7] R.Gutierrez-Osuna, J.A. Janet, and R.C. Luo, Modeling of ultrasonic range sensors for localization of autonomous mobile robot, *IEEE Transactions on Industrial Electronics,* Vol. 45 (1998) 654-662

[8] C-C. Tsai, A localization system of a mobile robot by fusing dead-rokening and ultrasonic measurements, *IEEE Transactions on Instrumentation and Measurement,* Vol. 47 (1998) 1399-1404

[9] C. F. Olson, Probabilistic self-localization for mobile robots, *IEEE Transactions on Robotics and Automation,* Vol. 16 (2000) 55-66

[10] P. Bonnifait and G. Garcia, Design and experimental validation of an odometric and goniometric localization system for outdoor robot vehicles, *IEEE Transactions on Robotics and Automation,* Vol. 14 (1998) 541-548

[11] S. Panzieri, F. Pascucci, and G. Ulivi, An outdoor navigation system using GPS and inertial platform, *IEEE/ASME Transactions on Mechatronics,* Vol. 7 (2002) 134-142

[12] A. Georgiev and P. K. Allen, Localization methods for a mobile robot in urban environments, *IEEE Transactions on Robotics,* Vol. 20 (2004) 851-864

[13] J.M. Lee, K. Son, M.C. Lee, J.W. Choi, S.H. Han, and M.H. Lee, Localization of a mobile robot using the image of a moving object, *IEEE Transactions on Industrial Electronics,* Vol. 50 (2003) 612-619

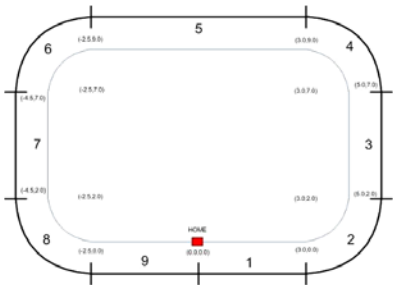
[14] J. Wolf, W. Burgard, and H. Barkhardt, Robust vision-based localization by combining an image-retrival system with monte carlo localization, *IEEE Transactions on Robotics,* Vol. 21 (2005) 208-215

[15] S. Se, D.G. Lowe, and J.J. Litle, Vision-based global localization and mapping for mobile robots, *IEEE Transactions on Robotics,* Vol. 21 (2005) 364-375

[16] J. Huang, S.M. Farritor, A. Qadi, and S. Goddard, Localization and follow-the-leader control of a heterogeneous group of mobile robots, *IEEE/ASME Transactions on Mechatronics,* Vol. 11 (2006) 205-215

Appendix A

Detail of path and measurement in experiment



STEP	Rear encoder				Steering encoder			X(M)	Y(M)
	L		R		Start	Stop	Result		
	Start	Stop	Start	Stop					
1	-15,311	4,958	-14,979	5,499	6	8	2	3.388074	0.035981
2	-15,440	21,408	-15,161	26,146	9	68	59	5.067132	2.506831
3	-22,419	41,606	22,130	47,120	11	13	2	5.029707	7.094204
4	-33,096	47,807	-37,031	53,454	9	67	58	3.105042	9.026133
5	857,378	971,341	977,453	1,101,919	-61	-59	2	-2.828483	8.990535
6	111,331	236,841	148,563	287,353	-63	1	62	-4.479611	-7.363039
7	292,321	451,222	350,262	524,803	-67	-63	4	-4.514433	1.752897
8	482,407	656,403	561,027	754,752	-64	-10	54	-2.413210	-0.021945
9	670,124	856,083	769,377	976,291	-61	-58	3	-0.291140	-0.006295