CONSTRUCTION OF A PROTOTYPE FREE-RANGING AGV SYSTEM

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ABSTRACT

The architecture and functions of a prototype free ranging AGV system are described in this paper. The system has single tricycle configuration - the front wheel is driven and steered simultaneously. The primary position measurement device of this system is the redundant encoder system - an absolute encoder for the steering angle measurement of the front wheel, two incremental encoders for the measurement of the rear wheel rotations. The secondary position measurement device is implemented to reduce the accumulated error in encoder measurements. The extended Kalman filter is suggested to combine the conflict measurement data for the proper position estimation.

1. INTRODUCTION

Significant efforts have been dedicated to the development of an industrial free-ranging AGV systems in universities and industries because of their favorable characteristics of reprogrammable guidepath, adaptability to highly flexible material handling requirements, and capability of immediate path changes.[1] The free-ranging AGV systems must be capable of locating its position, tracking the required material transport path, and arriving at the destined stations. These are related to the position estimation problems. The position of an AGV system may be described by three quantities - two rectangular coordinates (X, Y) of the reference point on the vehicle and the heading angle, Θ as shown in Fig 1.1, if the factory floor is relatively flat and smooth. The origin of the fixed reference coordinate system in Fig 1.1 is fixed somewhere in the environment.

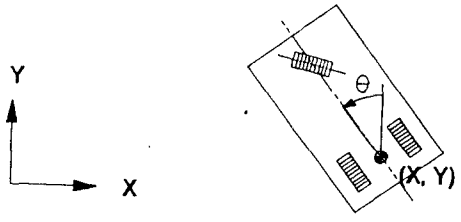

Fig. 1.1 Position Vector of an AGV System

The sensor systems for the position measurement of the free-ranging AGV are classified into two groups; relative and absolute sensors.[2,3] Relative sensors, including dead-reckoning and inertial navigation systems, measure the kinematic changes of the AGV system when the vehicle moves from one point to another in the working area.[4-7] The current position of the vehicle is then calculated based on those measurements and the previous vehicle's position. This type of sensors are very useful since they measure the AGV's position continuously as far as it moves. However, the position error becomes accumulative in proportional to the travelled distance of the vehicle. Absolute sensors, including beacon type sensor, ultrasonic sensors, and vision sensors, measure angle, distance, or relative position from the AGV system to landmarks fixed at known location.[8-13] The absolute position of the AGV in the environment is then calculated using trigonometric method or the coordinate transformation method based on these measurements. While the vehicle's position estimated by this type of sensors is accurate, they do not provide continuous knowledge of the vehicle's position because of their limited measurement ranges and/or field of view.

Development of multiple sensor systems, which combine information from both relative and absolute sensors, may be an alternative to solve the limit of the individual sensor system and to obtain reliable continuous position estimates.[14,15] The multiple sensor system arises the problem of handling the conflict position data resulting from measurement noise and external disturbance, and the problem of real time processing of sensor data resulting from the increased complexity of sensor system.[16,17]

The prototype free-ranging AGV uses both the relative and the absolute types of sensors - wheel encoders and the landmark tracking system - for the position estimation. The architecture of the hardware system is explained in detail. An integrating algorithm, which combines conflict measurement data from encoders and landmark tracking system, is proposed for the optimal position estimation.

2. HARDWARE SYSTEM

The hardware of the prototype AGV consists of several modules as shown in Fig. 2.1. The dead reckoning module, the landmark tracking module, driving control module, safety monitoring module, main controller are the examples of them. Intel 80286 CPU is used for the main controller and other modules are interfaced with the main controller through the IBM AT BUS.

The dead reckoning module consists of an absolute, two incremental encoders, and an interface board. The absolute encoder is directly attached to the front wheel and measures the angle of the front wheel - the steering angle of the vehicle. Since the absolute encoder generates 1024 pulses per turn, its angular accuracy is 0.35°. The incremental encoders are also directly connected to rear wheels and measure the rotations of rear wheels in sampling intervals. The diameter of rear wheel is 0.125 meters and the resolution of the encoder is 1024 pulses/turn. Thus, the unit pulse of the incremental encoder corresponds to 0.38 mm. The encoder interface board contains the up/down pulse detection circuit, up/down counter, latch, multiplexer, and 8255A IC chip.

The landmark tracking module consists of landmark, CCD camera, flash, flash actuating board, and image processing board as shown in Figure 2.2. The landmark is a rectangular plate with an equilateral right angled triangle at its center as shown in Fig. 2.3.

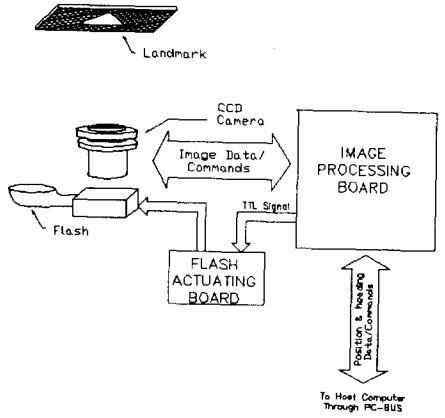

Fig. 2.2 Structure of Landmark Tracking System

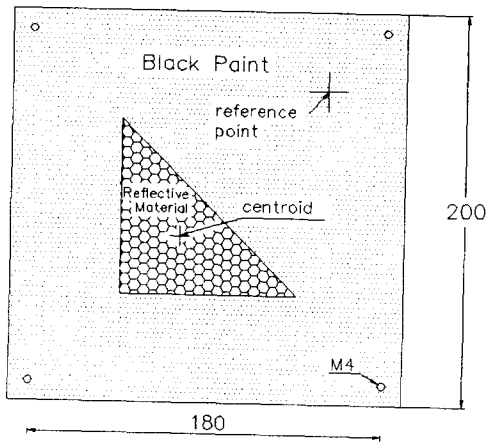

Fig. 2.3 Landmark Configuration

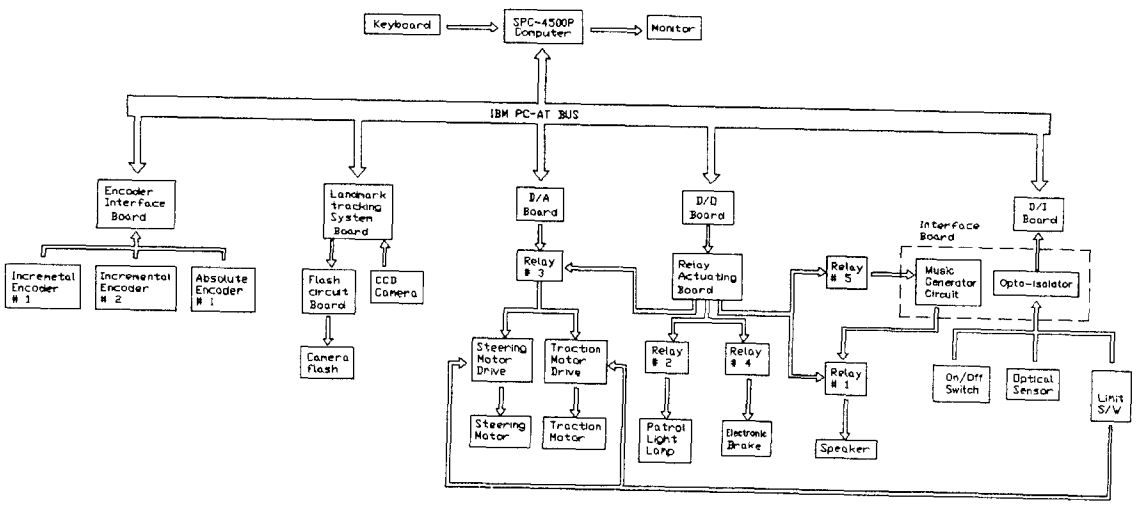

Fig. 2.1 Architecture of Hardware System

Retro-reflective material is used for the triangle shape in order to maximize amount of the reflected light from the landmark. The CCD camera has the pixel array of 192 x 165 pixels, image size of 2.64 x 2.64 mm, and uses the lens of 16 mm focal length. When the landmark is located on the ceiling 3 m away from the camera, the size of the FOV of the camera becomes 0.5 m x 0.5 m. The flash is used to provide illumination to the landmark and CCD camera. This combined with the retro-reflective landmark will help the CCD camera to get a clear image of the landmark. A ring-type flash light is installed in this system to supply uniform illumination. The image processing board plays a role of digitizing the video signal, extracting the boundary edge, and computing the position of the centroid and the orientation of the landmark image.

The driving control module consists of the motor driving board and two DC geared motors, one for the steering control and the other for the traction control. The main controller compares the encoder outputs with the desired values and commands the required signals through the D/A ports to the motor driving board based on the current error.

Safety module monitors the current vehicle status. The operations of Start S/W, Emergency Stop S/W, Manual/Auto S/W, Safety Bumper, Steering angle limiter are detected by numerous limit switches directed connected to them. The status of these limit switches are then informed to the main controller through the digital input ports. The main controller takes the right actions based on the vehicle status.

3. POSITION ESTIMATION SCHEME

3.1 Dead Reckoning System

Wheel encoder system is one of relative sensors which measure the motion changes of the wheeled AGV systems given some time interval. Define U_{1k} and U_{2k} the distance moved by the AGV and a half of the change of the heading angle of the vehicle between (k-1)-th and k-th sampling time of the encoders, respectively. Fig. 3.1 shows the parameters U_{1k} and U_{2k} graphically. These values are determined by the outputs of the encoder systems measured at the k-th sampling time.

Define S_{1k} and S_{2k} the distance moved by the right and left rear wheel of the AGV model, measured by the rear wheel encoders at k-th sampling time, respectively. Also define S_{3k} the steering angle measured by the front wheel encoders. The relationship of S_{ik} (i = 1,2,3)

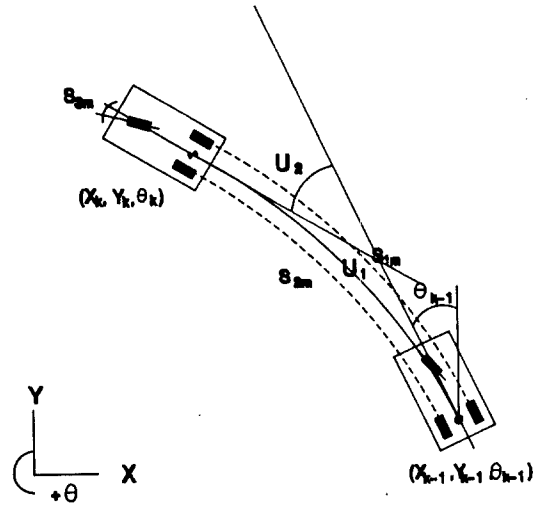

Fig. 3.1 Kinematic Relationship of U_{1k} and U_{2k}

and the displacement vector $\underline{U}_k$ (= $[U_{1k}\ U_{2k}]^T$) is derived as

$$S_{1k} = U_{1k} + W\ U_{2k} + e_{1k} \qquad (1)$$

$$S_{2k} = U_{1k} - W\ U_{2k} + e_{2k} \qquad (2)$$

$$S_{3k} = TAN^{-1}\{2\ L\ U_{2k}\ /\ U_{1k}\} + e_{3k} \qquad (3)$$

Where parameter e_i (i = 1,2,3) represents the measurement noise associated with each wheel encoder measurement and is considered to be uncorrelated Gaussian random noise. W and L indicate a half of the rear wheel spacing and the wheel base, respectively.

As shown in (1) and (2), the two-encoder system is sufficient to determine the displacement vector $\underline{U}_k$, thus our system has redundant information on $\underline{U}_k$. The linearized Maximum Likelihood estimation technique is found to be an efficient method to yield the best estimates of $\underline{U}_k$ from these redundant encoder measurements.

As shown in (3), S_{3k} is nonlinearly related with the displacement vector $\underline{U}_k$. The linearized version of (1) - (3) are

$$S_{1k} = U_{1k} + W\ U_{2k} + e_{1k}$$

$$S_{2k} = U_{1k} - W\ U_{2k} + e_{2k} \qquad (4)$$

$$S_{3k}^{D} = C_1\ U_{1k} + C_2\ U_{2k} + e_{3k}$$

Where C_1 and C_2 are constants determined by linearizing the equation (3) with respect to the reference values of U_{1k} and U_{2k}.

The value of $\underline{U}_k$ and its error covariance matrix R_U are obtained as

$$\underline{U}_k = (T_2^T R_2^{-1} T_2)^{-1} T_2^T R_2^{-1} \underline{S}_2$$

$$R_U = (T_2^T R_2^{-1} T_2)^{-1} \qquad (5)$$

Where

$$T_2 = \begin{vmatrix} 1 & W \\ 1 & -W \\ C_1 & C_2 \end{vmatrix}$$

$$\underline{S}_2 = [\ S_{1k}\ S_{2k}\ S_{3k}^D\ ]^T$$

R_2 = 3 x 3 covariance matrix of e_{1k}, e_{2k} and e_{3k}

With the assumption that the displacement of the AGV over a sample period is very small compared to vehicle dimensions, the current position of the AGV (X_k, Y_k, Θ_k) is calculated from the position at the previous sampling time (X_{k-1}, Y_{k-1}, Θ_{k-1}) and the values of U_{1k} and U_{2k} computed by equations (5).

$$X_k = X_{k-1} - U_{1k} \mathrm{SIN}(\ \Theta_{k-1} + U_{2k}\ ) + V_{1k}$$

$$Y_k = Y_{k-1} + U_{1k} \mathrm{COS}(\ \Theta_{k-1} + U_{2k}\ ) + V_{2k} \qquad (6)$$

$$\Theta_k = \Theta_{k-1} + 2\ U_{2k} + V_{3k}$$

Define the state vector $\underline{X}_k = [\ X_k\ Y_k\ \Theta_k\ ]^T$, the input vector $\underline{U}_k = [\ U_{1k}\ U_{2k}\ ]^T$, and the noise vector $\underline{V}_k = [\ V_{1k}\ V_{2k}\ V_{3k}\ ]^T$. The system noise vector $\underline{V}_k$ are produced by the uncertainty present in $\underline{U}_k$ and still preserve the characteristics of Gaussian distribution. The state vector representation of the equation (6) is

$$\underline{X}_k = \underline{f}\ \{\ \underline{X}_{k-1},\ \underline{U}_k\ \} + \underline{V}_k \qquad (7)$$

The vector function $\underline{f}\{\ \}$ indicates the nonlinear nature of the system equation, the position estimated from the relative sensor measurements. Equation (7) is now in the form of nonlinear stochastic equation, i.e. Gaussian - Markov equation. Equation (7) provides the continuous knowledge of position estimates. The method to compute the position estimate using (7) will be explained in the following section.

3.2 Landmark Tracking System

The landmark tracking system in our system is used to take pictures of the landmarks fixed on the ceiling when the landmark is within the field of view of the CCD camera. Then the image processing algorithm determines the location and orientation of the vehicle relative to the landmark.

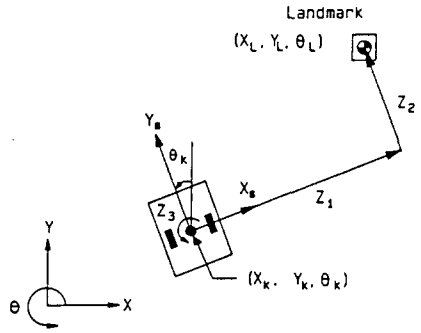

Fig. 3.2 Measurement Parameters of the Landmark Tracking System

Fig. 3.2 shows the measurement parameters of the vision camera and the landmark. In this case, the relationship of the measurement parameters and the vehicle position becomes

$$Z_1 = (X_L - X_k)\mathrm{COS}(\Theta_k) + (Y_L - Y_k)\mathrm{SIN}(\Theta_k) + W_1 \qquad (8)$$

$$Z_2 = -(X_L - X_k)\mathrm{SIN}(\Theta_k) + (Y_L - Y_k)\mathrm{COS}(\Theta_k) + W_2 \qquad (9)$$

$$Z_3 = \Theta_L - \Theta_k + W_3 \qquad (10)$$

Measurement parameters Z_1 and Z_2 are the displacement of the landmark along the X- and Y-axis of the vehicle coordinate system (in this case, the origin of the vehicle frame is located at the reference point of the AGV), respectively. Z_3 is the orientation of the vehicle relative to the landmark. The coordinates and orientation of the landmark in the global coordinate system are notated as (X_L, Y_L) and Θ_L, respectively. The position vector $\underline{X}_k$ at the instance of absolute sensor measurement is the parameter we want to know in this case, but the measurement noise prohibits direct computation of the value of the vehicle's position from (8) - (10). Equations (11) is a general form of the measurement equations (8) - (10).

$$\underline{Z}_k = \underline{h}\ \{\ \underline{X}_k\ \} + \underline{W}_k \qquad (11)$$

The vector function $\underline{h}\{\ \}$ reflects the nonlinear nature of measurement equations. In (11), $\underline{Z}_k$ is the measurement vector and $\underline{W}_k$ is the measurement noise vector.

4. SENSOR DATA FUSION ALGORITHM

Two kinds of sensor systems, wheel encoders and vision camera, are used to find the position estimates of free-ranging AGV systems in this

work. Because of the limited size of the field of view of the camera the vision sensor measures the vehicle's position occasionally, only when any landmark is located inside its field of view. In a region where both relative sensors and absolute sensor deliver information of the vehicle's position simultaneously, it is necessary to develop a robust estimation algorithm which filter those noisy sensor data and find the optimal position estimate intelligently. An extended Kalman filter estimation algorithm is implemented for the purpose of the optimal estimation of the position in this paper.

The position estimates obtained from the wheel encoder measurements are shown in ((12) and the propagation of the error covariance in the estimates is shown in (13).

$$\underline{X}_k^- = \underline{f}_k\{ \underline{X}_{k-1}^+, \underline{U}_k \} + E\{\underline{V}_k\} \qquad (12)$$

$$M_k = F_k P_{k-1} F_k^T + Q_k \qquad (13)$$

Where

$\underline{X}_k^-$ = Position estimated by wheel encoder measurements at k-th sampling time.

$\underline{X}_{k-1}^+$ = Position estimated at (k-1)-th sampling time.

M_k = Error covariance matrix of $\underline{X}_k^-$

F_k = Coefficient matrix obtained by the linearization of the system equation.

$$F_k = \begin{vmatrix} 1 & 0 & -U_{1k}\,\mathrm{COS}(\Theta_{k-1}^+ + U_{2k}) \\ 0 & 1 & -U_{1k}\,\mathrm{SIN}(\Theta_{k-1}^+ + U_{2k}) \\ 0 & 0 & 1 \end{vmatrix}$$

Q_k = Covariance matrix of $\underline{V}_k$ at k-th sampling time.

P_{k-1} = Error covariance matrix of $\underline{X}_{k-1}^+$.

When the AGV travels in regions where both relative and absolute sensors work, the position estimates are obtained as

$$K_k = M_k H_k H_k^T [H_k M_k H_k^T + R_k]^{-1} \qquad (14)$$

$$\underline{X}_k^+ = \underline{X}_k^- + K_k \{ \underline{Z}_k - \underline{h}_k(\underline{X}_k^-) \} \qquad (15)$$

$$P_k = [I-K_k H_k] M_k [I-K_k H_k]^T + K_k R_k K_k^T \qquad (16)$$

Where

K_k = Kalman gain

$\underline{X}_k^+$ = Position vector estimated by the combination of wheel encoder and vision sensor measurements at k-th sampling time.

P_k = Error covariance matrix of $\underline{X}_k^+$.

I = 3 x 3 identity matrix.

R_k = Covariance matrix of measurement noise vector.

H_k = Coefficient matrix obtained by linearizing the measurement equation.

$$H_k = \begin{vmatrix} -\cos\Theta_k^- & -\sin\Theta_k^- - (X_L - X_k)\sin\Theta_k^- + (Y_L - Y_k)\cos\Theta_k^- \\ \sin\Theta_k^- & -\cos\Theta_k^- - (X_L - X_k)\cos\Theta_k^- - (Y_L - Y_k)\sin\Theta_k^- \\ 0 \quad 0 & 1 \end{vmatrix}$$

When the position is estimated only by the encoder readings, in the equation (12), $\underline{X}_{k-1}^+$ is substituted with $\underline{X}_{k-1}^-$ and in the equation (13), P_{k-1} is sunstituted with M_{k-1}.

5. CONCLUSION

The prototype AGV system is constructed to demonstrate the free ranging capability. Since the successfulness of the free-ranging AGV system depends on the precision of the position measurement system, multiple sensor systems are suggested to enhance the accuracy of the position estimation. An integrating algorithm, which combines the redundant encoder system and the landmark tracking system, is proposed using the extended Kalman filter.

The future work will be focused on the experimental verification of the proposed position estimation algorithm.

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