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VEHICLE AUTOMATION SYSTEM BASED ON MULTI-SENSOR INTEGRATION

by

N. Noguchi
Associate Professor
Bioproduction Enginering
Hokkaido University, Sapporo, JAPAN.

J.F. Reid
Professor
Agricultural Engineering
University of Illinois, Urbana-Champaign Urbana, IL

J. Will
Graduate Student
Electrical Engineering
University of Illinois, Urbana-Champaign, Urbana, IL

E.R.Benson
Graduate Student
Agricultural Engineering
University of Illinois, Urbana-Champaign Urbana, IL

T.S. Stombaugh
Food, Agricultural and Biological Engineering
Ohio State University, OH

Summary:
The purpose of the study is to develop the guidance system by the sensor fusion integration with a machine vision, an RTK-GPS and a geometric direction sensor (GDS). The Extended Kalman Filter (EKF) and a statistical method based on two-dimensional Probability Density Function are adopted as a fusion integration methodology in this research. To achieve the navigation planner based on sensor fusion integration, the four types of control strategies were built by changing combination of three kinds of sensors; machine vision, the RTK-GPS and the GDS. The developed navigation planner involves the priority scheme of the control strategies by knowledge-base approach. The average lateral error of the vehicle guidance based on the fusion of the RTK-GPS and the GDS indicated 8.4 cm. Because the lateral error was less than 20 cm which was the accuracy of the RTK-GPS, the developed sensor fusion methodology with the EKF was seemed to be satisfactory operation.

Keywords:
Vehicle automation, Sensor fusin, Machine vision, Extended kalman filter

INTRODUCTION

As the 21st century approaches, it is very important to develop the production technology required to decrease the cost of food production and to ensure a stable food supply. In advanced countries, the lack of labor and aging work force complicate the situation. To solve these problems, vehicle guidance system that can reduce operator's fatigue will play an important role in the next century. In particular, the vehicle guidance systems provide for more efficient work and reduction of production costs (Noguchi, 1995). However, because the environment in which the guidance system is used is an outdoor space with many disturbances resulting from variable soil and weather conditions, there are many problems in developing a robust vehicle guidance system for crop production. Machine vision that has high possibility for the guidance has been widely investigated to utilize as a sensor of the guidance system (Reid, 1987, Marchant, 1997, Billingsley 1997). However, row detection by the image processing in the outdoor environment, which includes various disturbances such as shadow, weed infestation and various soil colors and types, still has fairly difficult problems. Recently, there has been some research, which explores the possibility for an RTK-GPS for the vehicle guidance system, because of the decreasing costs of RTK-GPS while the positioning accuracy is improving. But, RTK-GPS also has low reliability caused by the interference of the GPS signals by trees and buildings. Therefore, to improve stability of the system, redundant sensing systems are desirable for a navigation system used on the field.

The purpose of the study was to develop the guidance system by sensor fusion integration with machine vision, RTK-GPS and geometric a direction sensor (GDS). The Extended Kalman Filter (EKF) and two-dimensional Probability Density Function (PDF) are adopted as the fusion integration methodology in the research.

MATERIALS AND METHOD

1. The test equipment

The test vehicle is a conventional 115-kW tractor (CASE-IH, 7220) with a modified computer controlled electrohydraulic steering system. The tractor system has machine vision, GDS and RTK-GPS (**Fig.1**). Machine vision is composed of a bmonochrome CCD camera, and a frame grabber (CX-100, Image Nation). A near infrared filter (800 nm) is installed on the camera to improve discrimination between the plant material and soil. The camera is mounted on the centerline of the test vehicle, with a 20 degree down angle. In addition, the navigation sensors on the vehicle included a geomagnetic direction sensor (**Fig. 2**) and DGPS.

An RTK GPS (RT-20, Novatel) was used as global positioning system. RTK-GPS achieve an accuracy less than 20cm with a 5Hz-update rate. GDS is utilized to detect the heading angle of the vehicle. Because of the low cost and lack of output drift, GDS has recently been used as a sensor for vehicle heading angles in many research projects (Yukumoto, 1995, Noguchi, 1997). But, there is a serious problem in using GDS as a heading angle sensor. The problem is that errors can result from the magnetism, which exists around GDS. GDS is able to detect weak geomagnetic field, which is warped by the metal frame of the vehicle and mounted electrical apparatus such as the computer and the electromagnetic steering valve around GDS. Therefore, it is necessary to refine the warp of the magnetic field so as to precisely identify the two dimensional vector of geomagnetism by using GDS. **Fig.3** shows the warp of a magnetic field around GDS. The output x and y from GDS were continuously obtained by travelling steady-state circle turn on a flat field. In theory, a trajectory of E_x and E_y should describe a circle, and the center of the circle should correspond with the origin of the coordinate axes. However, the center of the E_x and E_y sifted to the coordinate of (0, 1500) as a consequence of the magnetism which exists around the vehicle. In the research, the offset of E_x and E_y was considered to detect an accurate heading angle.

2. Navigation System by Sensor Fusion Integration

The developed vehicle automation system is shown in **Fig.4**. To develop a robust navigation planner, four types of control Strategy were built by changing combination of three kinds of sensors; machine vision, RTK-GPS and GDS. Each control Strategy includes the priority order based on the sensor reliability.

Combining all sensor information is attained by the control method named as Strategy-1. As mentioned previously, GDS can provide the heading angle as well as machine vision, while the lateral error can be calculated from both RTK-GPS and machine vision. Therefore, the sensor fusion integration methodology based on a Probability Density Function (PDF) was developed to avoid redundant navigation signals. Strategy-2 is able to control the steering angle based on navigation signals created by machine vision. To remove the Gaussian noise from the detected lateral error and heading error, an Extended Kalman Filter (EKF) was plugged into the control module. And, combination of RTK-GPS and GDS provided control Strategy-3. The EKF was adopted in the module to remove the observation noise as well as the Strategy-2. If information from these sensors, i.e. machine vision and RTK-GPS would be invalid by unexpected error, then Strategy-4 provides the appropriate steering angle by GDS alone is chosen as the steering controller.

To determine the most appropriate control Strategy during travel, a layered control system was built. The upper layer manages the control strategies, and decides the appropriate control Strategy during travel. On the other hand, the lower layer can calculate the steering angle based on the lateral error and the heading error for each control Strategy. Since the data string from machine vision and RTK-GPS includes values, which describes the data reliability, the upper layer controller can decide the appropriate Strategy based on the information from these sensors.

3. Extended Kalman Filter (EKF)

As mentioned above, Strategy-2 and –3 involved the EKF for integrating the sensor information. The EKF, which we utilized, is briefly explained here. From **Fig. 5**, the basic vehicle movement can be explained as

$$mV\left(\frac{db}{dt}+r\right)=Y_f+Y_r \tag{1}$$

$$I\frac{dr}{dt}=l_f Y_f+l_r Y_r \tag{2}$$

where, m and I are the mass and the moment of inertial of the tractor, respectively. b is lateral slip, r is yaw rate, l_f is the distance from the front axis to the center of the gravity, and, l_r is the distance from the rear axis to the center of the gravity. Y_f and Y_r is lateral force on the front and rear tires. The equation of state is described as follows:

$$\dot{X} = (b, r) \tag{3}$$

$$\dot{X} = AX + Bu \tag{4}$$

$$A = \begin{bmatrix} \dfrac{-k_f + k_r}{mV} & \dfrac{-k_f l_f + k_r l_r - mV^2}{mV^2} \\ \dfrac{-k_f l_f - k_r l_r}{I} & \dfrac{-k_f l_f^2 - k_r l_r^2}{I} \end{bmatrix} \tag{5}$$

$$B = \begin{bmatrix} \dfrac{k_f}{mV} & \dfrac{k_f l_f}{I} \end{bmatrix}^T \tag{6}$$

where, X is state vector and u is control vector which is the steering angle.

The vehicle model was converted from continuity equations to discrete equations and linearlized as follows.

$$\hat{X}(k+1) = \hat{\Phi}\,\hat{X}(k) + \hat{\Gamma}u(k) \tag{7}$$

$$Y(k+1) = C\hat{X}(k+1) \tag{8}$$

$$\hat{\Phi} = e^{AT} = L^{-1}(sI - A)^{-1} \tag{9}$$

The Kalman gains K and estimated state vector $\hat{X}$ shown in **Fig.6** can be calculated as

$$\hat{X}(k+1) = \hat{\Phi}\,\hat{X}(k) + \hat{\Gamma}u(k) + K(k)\left(y(k) - C\,\hat{X}(k) \right) \tag{10}$$

$$K(k) = \hat{\Phi}\,P(k)\,\hat{\Phi}^T + \left(R + CP(k)C^T\right)^{-1} \tag{11}$$

$$P(k+1) = \hat{\Phi}\,P(k)\,\hat{\Phi}^T - \hat{\Phi}\,P(k)\,C^T\left(R + CP(k)C^T\right)^{-1} \tag{12}$$

$$R = \begin{bmatrix} s_{GPS}^2 & 0 \\ 0 & s_{GDS}^2 \end{bmatrix} \qquad \text{(For GPS and GDS)} \tag{13}$$

$$R = \begin{bmatrix} s_{offset,VISION}^2 & 0 \\ 0 & s_{heading,VISION}^2 \end{bmatrix} \qquad \text{(For Vision)} \tag{14}$$

where, *R* is covariance matrix. $\hat{\Phi}, \hat{\Gamma}$ are discrete state vector and discrete control vector, respectively. By plugging the EKF into the each control module, the gaussian nose included in the navigation signals is removed.

4. Steering controller

To control the vehicle accurately, steering angle was determined using a feedback technique with two measurements of the displacement *Dr* and the heading angle f. The steering angle y can be calculated by:

$$y = a\Delta r + b\left(f_d - f\right) \tag{15}$$

where f_d is the path direction of GDS and f is the measured heading angle. The gains (a and b) were experimentally determined to achieve satisfactory control stability and accuracy.

In addition, if the vehicle cannot receive the lateral error from RTK-GPS or machine vision, the vehicle is also able to travel by using only the information from GDS. Ignoring lateral slip, the lateral error *Dr* for the desired path can be calculated by:

$$\Delta f = f - f_d \tag{16}$$

$$\Delta e = v \sin \Delta f \tag{17}$$

$$\Delta r = \sum_k \Delta e_k \tag{18}$$

where, *De* is the incremental lateral displacement, and *v* is the traveling velocity. Therefore, the feedback controller of the steering angle y can be expressed as:

$$y = a\Delta r^* + b\left(f_d - f\right) \tag{19}$$

where *a¢* and *b¢* are the control gains.

RESULTS

The result of the vehicle automation by the control Strategy-3, which combines RTK-GPS with GDS, is shown in **Fig.7**. The test was conducted under the straight line path at the velocity of 8.2 km/h. The average lateral error of the vehicle guidance based on the control Strategy-3 was 8.4 cm. Because the lateral error was less than 20 cm which was the accuracy of RTK-GPS, the developed EKF was seemed to be satisfied and operated properly. However, the error average, which reached 12.9cm, was recognized as a bias error. The bias error might be raised from the disagreement of the coordinate axes between GDS and RTK-GPS, and the measurement and control accuracy of the steering angles.

The control result of Strategy-3, when giving 20 º initial heading error is shown in **Fig.8**. The convergence of the lateral error and heading error was obtained after about 20m travel. It was clear that the controller performance of Strategy-3 was satisfied.

The result of the vehicle automation by the control Strategy-4 which utilized GDS alone is shown in **Fig.9**. The travel velocity is 8.2 km/h, which is same with the test of the control Strategy-3. The lateral error accumulates due to the controller using only heading error, which is a kind of dead reckoning. However, the average error and the standard deviation were 3.9cm and 8.4cm, respectively. It was concluded that the control Strategy-4 can be used as the short-term controller in emergency situations.

CONCLUSIONS

To develop the robust guidance system by the sensor fusion integration with machine vision, RTK-GPS and geometric direction sensor (GDS), an Extended Kalman Filter (EKF) and a Probability Density Function (PDF) were adopted as fusion integration methodology in the research. To achieve the navigation planner based on sensor fusion integration, four types of control strategies were built by changing combination of three kinds of sensors; machine vision, RTK-GPS and GDS. The developed navigation planner involved the priority scheme of the control strategies by knowledge-base approach. The average lateral error of the vehicle guidance based on the control Strategy-3 indicated 8.4 cm. Because the lateral error was less than 20 cm which was the accuracy of RTK-GPS, the developed sensor fusion methodology with the EKF operated satisfactorily.

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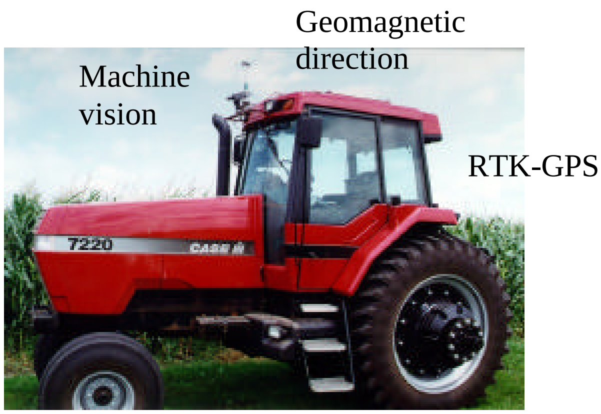


Fig.1 Test tractor for vehicle automation

Fig.2 Overview of GDS

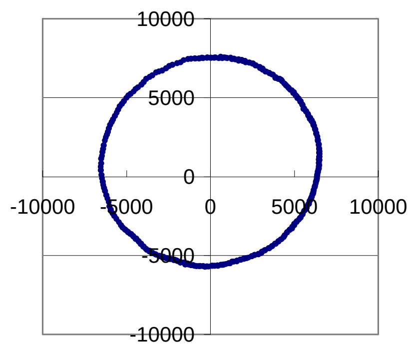


Fig.3 GDS output characteristics

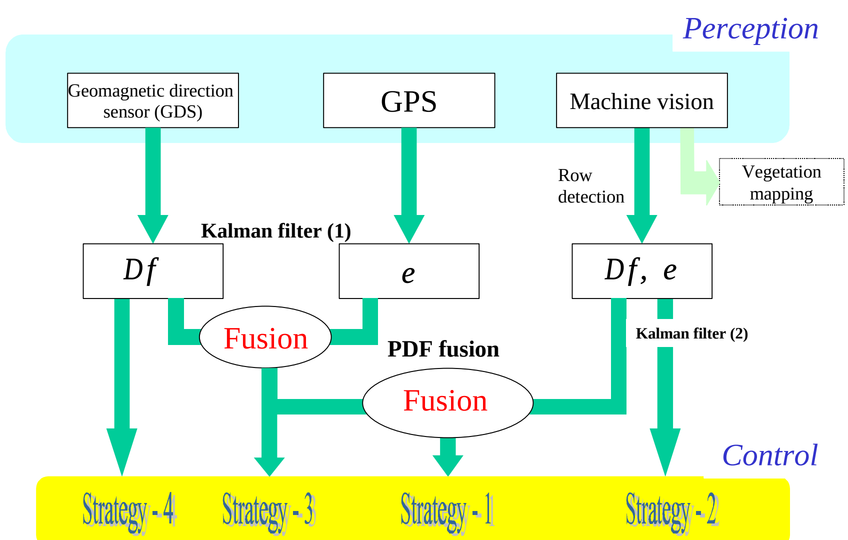
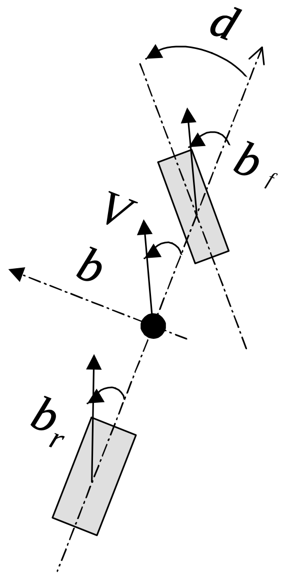


Fig. 4 Concept of the sensor fusion integration for vehicle guidance



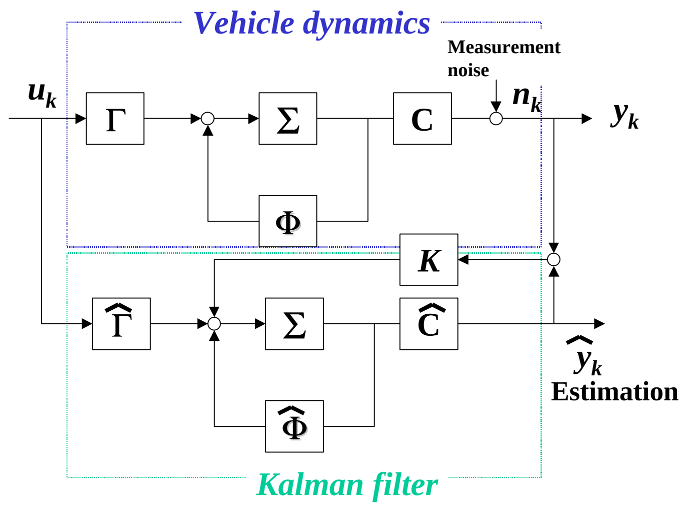


Fig. 5 Vehicle dynamics model

Fig. 6 Extended Kalman Filter construction

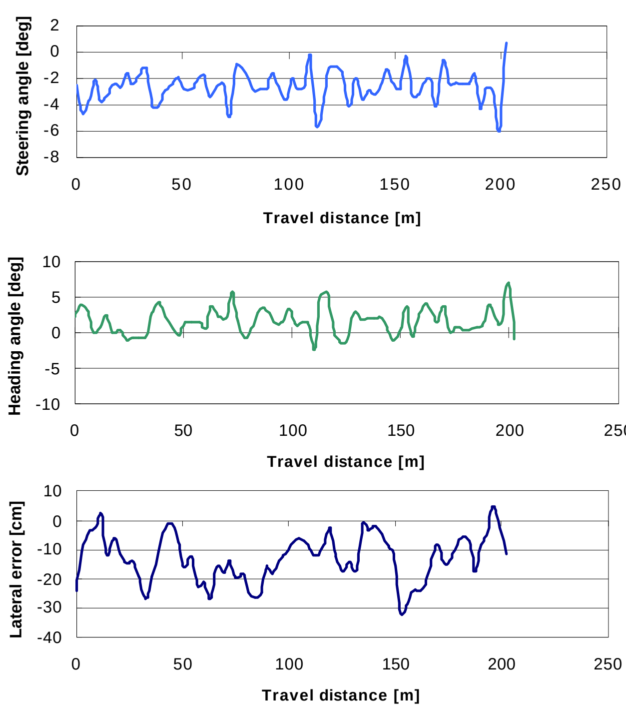


Fig. 7 Vehicle guidance characteristics of the control Strategy-3 on the straight path

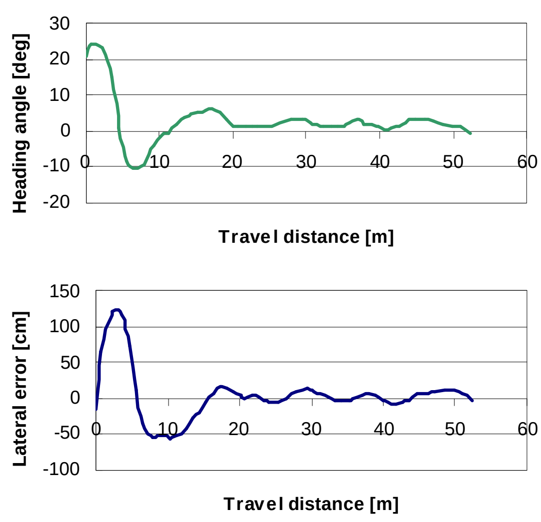


Fig. 8 Control process of the control Strategy-3

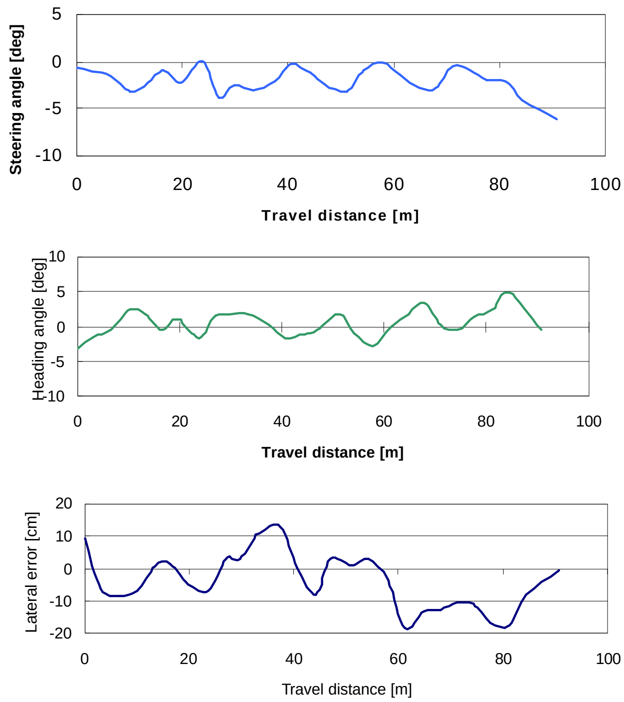


Fig. 9 Vehicle guidance characteristics of the control Strategy-4 on the straight path