Attitude Angle Estimation for Agricultural Robot Navigation Based on Sensor Fusion with a low-cost IMU

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Abstract: The objective of this research was to explore the use of data information of a low-cost IMU to provide an attitude angle with acceptable accuracy for agricultural robot navigation. This work was an attempt to create attitude angle estimation system via sensor fusion method based on gyroscope and accelerometer in this low-cost IMU. The used algorithm processed and integrated the data from triple gyroscope and tri-axis accelerometer using a low-pass filter and Kalman filter. Under this algorithm, experiment data showed that the estimation precision was improved effectively. It can solve noise jamming, and realize attitude angle optimal estimation.

Keywords: Kalman Filter; Low-Pass Filter; Sensor Fusion; Attitude Estimation; IMU Sensor.

1. INTRODUCTION

In autonomous navigation field, it is necessary to obtain the attitude and position of agricultural robot. It is the basic of navigation control. Only on this basis, we can continue to carry out the further work, such as path planning or obstacle avoidance. Consequently, a suitable sensor is needed to calculate the attitude of the agricultural robot. An inertial measurement unit (IMU) is such a sensor to measure the attitude in three axes. The IMU, as one kind of navigation sensor, working with global positioning system(GPS), geomagnetic direction sensor(GDS), or machine vision, is widely used in the robot navigation field today.

Normally, an IMU calculates the attitude based on two parts in its body. One is the gyroscope, and the other is the accelerometer. There are no problems to get the attitude angle just by three axes gyroscope, but it depends on the measurement accuracy of the IMU. At the same time, the system error will be accumulated with time. It could not be competent to work long time. In addition, the agricultural robot runs in variable speeds, so the data measured only by accelerometer will mix with strong noise. It is not appropriate for calculating the attitude angle. Using the fiber optic gyroscopes-based IMU can solve the problem, but it is costly for a navigation sensor of an agricultural robot, which is not conducive to the commercialization and popularization of agricultural robot. In order to be economically acceptable to the farmers the application of the robot farming system, a low-cost navigation system is necessary to consider(Noguchi, 2011).

The objective of this paper was to explore the use of data information of a low-cost IMU to provide an attitude angle with acceptable accuracy for agricultural robot navigation. The data processing was to use sensor fusion principle via integrating the data from gyroscope and accelerometer in this IMU. It included a low-pass filter and a Kalman filter. The experiment performance showed that it can solve noise jamming and realize attitude angle optimal estimation.

2. MATERIALS AND METHODS

2.1 Inertial Measurement Sensor

A small low-cost IMU (Fig. 1) from Seiko Epson Corporation was used as the inertial sensor on the agricultural robot for this research. This IMU with six degrees of freedom is very compact of 24*24*10 mm, 7 grams. Fig. 2 shows the block diagram of this IMU. It is composed of a triaxial quartz micro electro mechanical systems(QMEMS) gyroscope with a triaxial micro electro mechanical systems(MEMS) accelerometer. The outputs of this IMU include chip temperature, triaxial angular rates and linear accelerations. The main performance and electrical specifications shows in Table.1(Epson IMU datasheet, 2011).

Fig. 1 The appearance of the low-cost IMU

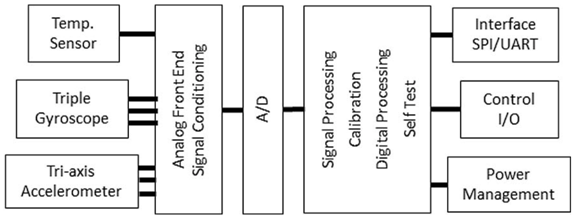


Fig. 2 The block diagram of the IMU

Table 1. Main Performance & Electrical Specifications

Parameters	Typ.	Unit
GYROSCOPE		
Dynamic Range	±300	deg/s
Initial Error	0.5	deg/s
In-Run Bias Stability	6	deg/hr
Angular Random Walk	0.2	deg/√hr
Noise Density	0.004	(deg/s)/ √Hz, rms
ACCELEROMETER		
Dynamic Range	±3	G
Initial Error	8	mG
In-Run Bias Stability	0.1	mG
Velocity Random Walk	0.04	(mG/sec)/ √hr
Noise Density	0.06	mG/√Hz, rms

An accelerometer in this low-cost IMU was used for measuring the triaxial linear acceleration. In the nature, as we know, the gravity acceleration vector always directs to the center of the earth. Fig. 3 shows the coordinated frame of this IMU. The measured value of accelerometer is the projection addition of gravity acceleration and absolute acceleration(Chen Jengheng,1994). So when the IMU keeps static, the relationship between the output value of accelerometer and slant angle (Roll, Pitch) is not linear, but trigonometric function. Fig.4, shows the trigonometric function relationship in pitch direction.

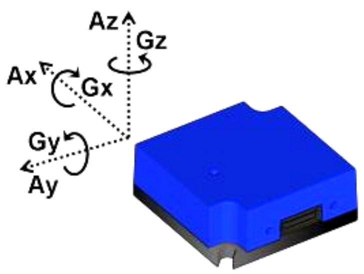


Fig.3 The coordinated frame of the IMU

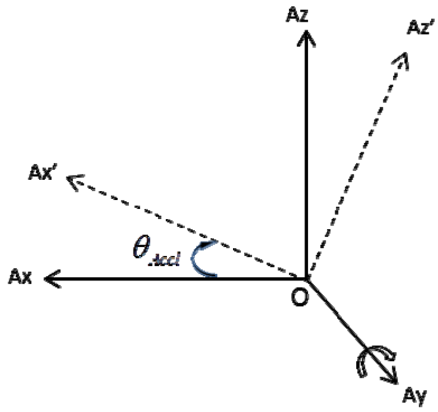


Fig. 4 The trigonometric function relation in pitch direction

The Ax-O-Az plane was rotated about θ_{Accl} degree around Ay-axis. According to Fig.4, pitch θ_{Accl} was calculated by using (1).

$$\tan\theta_{\text{Accl}} = Accl_x / Accl_z \tag{1}$$

where, $Accl_x$ is the acceleration in Ax' direction, and $Accl_y$ is the acceleration in Az' direction.

To obtain the pitch θ_{Accl} , inverse trigonometric function processing should be done by using (2).

$$\theta_{\text{Accl}} = \arctan\left(Accl_x / Accl_z\right) \tag{2}$$

With the same trigonometric function, roll can be also calculated. However, yaw is in the horizontal plane. It is orthogonal with gravity acceleration. So it is unable to get the projection on horizontal plane, namely, yaw cannot be calculated from the accelerometer.

In addition, the environment where the agricultural robot works is complex. And the motion of the agricultural robot itself is changed rapidly in real time. The high frequency measurement noise is included. It is necessary to design a low-pass filter to make the acceleration data smooth. There are many classic low-pass filters. Here, we chose a weighted average filter to pre-process the measured value of the triaxial accelerometer in this low-cost IMU. The acceleration value at time *t* was calculated based on the weighted average value from time *t* to t-5 by using (3).

$$\overline{Accl} = (Accl_t + Accl_{t\text{-}1} + Accl_{t\text{-}2} + Accl_{t\text{-}3} + Accl_{t\text{-}4} + Accl_{t\text{-}5})/6 \tag{3}$$

where $\overline{Accl}$ is the output value at time *t* after the data was processed.

The gyroscope can measure the rotation rate of IMU. So the triaxial slant angle θ_{Gyro} could be obtained via rotation rate integral by using (4). Because of the temperature variation, unstable moment of force and noise jamming, the gyroscope will generate drift error which will become bigger and bigger with time, which can be seen in (5).

$$\theta_{\text{Gyro}} = \int \omega \cdot dt \tag{4}$$

$$\theta_{\mathrm{Gyro}} = \int (\omega + \sigma) \cdot dt \tag{5}$$

where ω is the measured angular rate, σ is the measured noise, and t is the gyroscope measurement sampling period.

According to the analysis above, the conclusion is that using accelerometer or gyroscope alone to calculate the attitude angle is not suitable.

2.2 Sensor Fusion Method

Sensor fusion is desirable on exerting the advantages of accelerometer and gyroscope. Here, we used Kalman filter to integrate the data from both accelerometer and gyroscope. Fig.5 shows the block diagram of sensor fusion method processing.

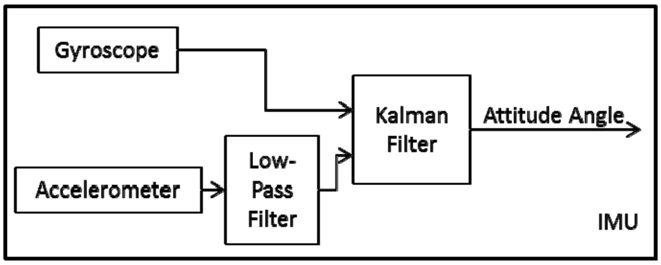


Fig. 5 The block diagram of sensor fusion method

The Kalman filter is optimal when the process noise and the measurement noise can be modelized by white Gaussian noise(Mathieu St-Pierre, 2004). As mentioned earlier, the relationship between slant angle and angular rate is derivative relations. The real slant angle φ can be used to make a state equation as (6) and measurement equation as (7).

$$\begin{bmatrix} \dot{\varphi} \\ \dot{b} \end{bmatrix} = \begin{bmatrix} 0 & -1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \varphi \\ b \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} \omega_{Gyro} + \begin{bmatrix} \sigma_{Gyro} \\ 0 \end{bmatrix} \tag{6}$$

$$\varphi_{Accl} = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} \varphi \\ b \end{bmatrix} + \sigma_{Accl} \tag{7}$$

where ω_{Gyro} is the angular rate with bias, φ_{Accl} is the angle calculated from accelerometer by using (2) and (3) via low-pass filter, σ_{Gyro} is the measurement noise of gyroscope, σ_{Accl} is the measurement noise of accelerometer, and b is the drift error of gyroscope. T_s is set up as system sampling period. Equation (8) is the state equation of discrete-time system.

$$\mathrm{X(k \mid k-1) = A \cdot X(k-1 \mid k-1) + B \cdot U(k)} \tag{8}$$

where *A* is system transition matrix $A = \begin{bmatrix} 1 & Ts \\ 0 & 1 \end{bmatrix}$, *B* is system control matrix $B = \begin{bmatrix} Ts \\ 0 \end{bmatrix}$, *X(k|k-1)* is the system state in moment k estimated by state k-1. *U(k)* is exogenous control input in moment k. *P(k|k-1)* is the priori estimate error covariance of *X(k|k-1) as (9).*

$$\mathrm{P(k \mid k-1) = A \cdot P(k-1 \mid k-1) \cdot A^T} + Q \tag{9}$$

where Q is covariance matrix of system process noise $Q = \begin{bmatrix} q\_accl & 0 \\ 0 & q\_gyro \end{bmatrix}$, which q_accl is the covariance of accelerometer and q_gyro is the covariance of gyroscope. Matrix $\mathrm{A^T}$ is the transpose of matrix *A.*

The optimal estimate *X(k | k)* in state *k* is calculated by using (10)

$$X\mathrm{(k \mid k) = X(k \mid k-1)} + k_g\mathrm{(k)} \cdot (Z\mathrm{(k)} - \mathrm{H \cdot X(k \mid k-1)}) \tag{10}$$

where *H* is observation matrix, H=[1 0]. $k_g(k)$ is Kalman gain derived from minimizing the posteriori error covariance by using (11).

$$\mathrm{k_g(k) = P(k \mid k-1) \cdot H^T / (H \cdot P(k \mid k-1) \cdot H^T + R)} \tag{11}$$

where *R* is covariance matrix of measuring error from accelerometer. In order to make the Kalman filter update, we should update the covariance equation by using (12).

$$\mathrm{P(k \mid k)} = (I - k_g\mathrm{(k)} \cdot H) \cdot P\mathrm{(k \mid k-1)} \tag{12}$$

where I is Unit matrix $I = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$.

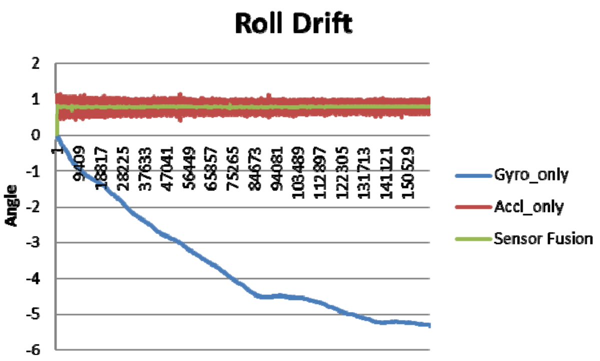
Above these, based on recursive functions from (8) to (12), keep calculating until finding the optimal estimate attitude angle value.

3. RESULTS AND DISCUSSION

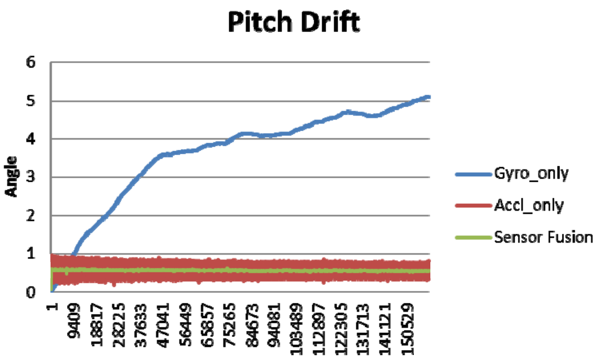
In order to verity the validity of the sensor fusion method via low-pass filtering and Kalman filtering better than one sensor, no matter which is used in attitude angle estimation, gyroscope or accelerometer, two parameters were chosen to analyse it. One was drift error and the other was dynamic attitude angle estimation.

3.1 Drift Error

The drift error is directly related to the measurement accuracy and stability of the measurement system. Here, we compared the performances among gyroscope-only, accelerometer-only and sensor fusion integration by the two sensors. Fig. 6 shows the result of drift in 20 minutes. In the coordinate system, abscissa is the measurement samples in twenty minutes. Ordinate is the drift angle, with degree as the unit.



a) The drift in roll direction

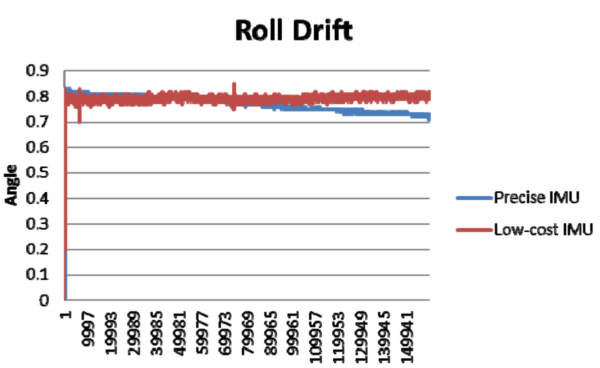


b) The drift in pitch direction

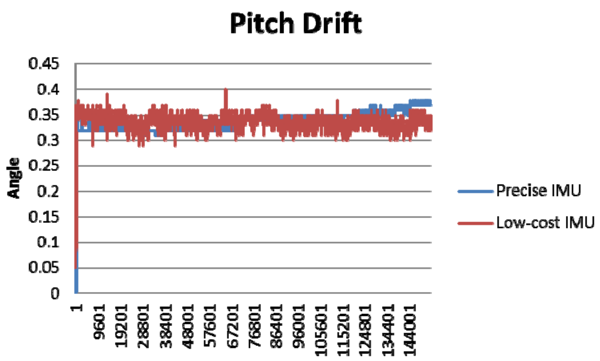
Fig. 6 The drift from gyroscope, accelerometer and sensor fusion

From Fig. 6, because of the integral error accumulation, the drift just measured by gyroscope increases continuously. Otherwise, the drift measured by accelerometer does not increased with time, but the drift oscillation is in one biggish area. Whereas, under sensor fusion method, the drift is almost zero. It is also smoother than the data from accelerometer.

It was found that the drift under sensor fusion method was superior to the other two single sensor methods. So, based on this sensor fusion method, we compared the drift performance between this low-cost IMU and a precise IMU manufactured by Japan Aviation Electronics Industry, Ltd, which can output attitude angles directly.



a) The drift in roll direction



b) The drift in pitch direction

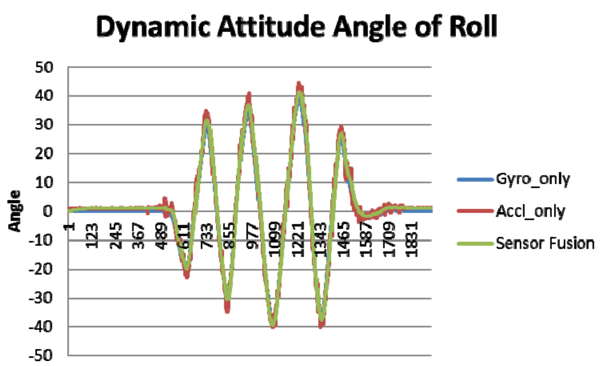
Fig. 7 The drift from the low-cost IMU and the precise IMU

The precise IMU and the low-cost IMU were fixed on the same plane and performed and logged the drift data. Fig.7 shows one result of the experiments. The drift data of these two IMUs is logged in 20 minutes. In the coordinate system, abscissa is the sample with time, ordinate is the drift angle, with degree as the unit. The reason why the output had a tiny angle is that we cannot guarantee the absolute level of the plane.

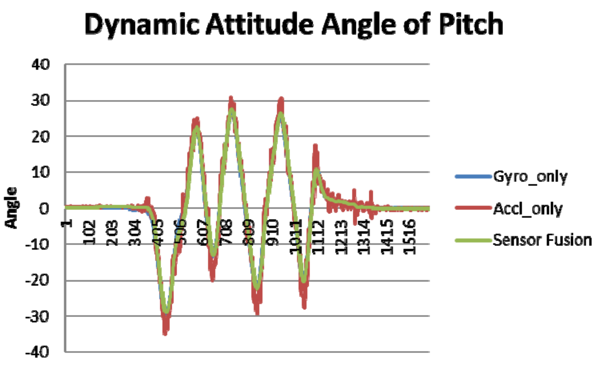
3.2 Dynamic Attitude Angle

The IMU set up on the agricultural robot is used mainly for logging the attitude state and correcting the heading angle of the working agricultural robot. So the Dynamic characteristic of the IMU is very important to the agricultural robot navigation.

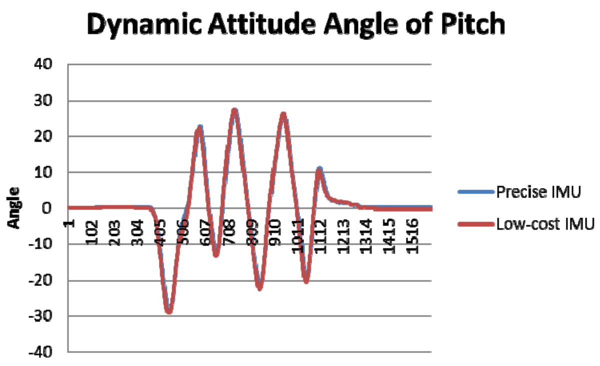
We logged the dynamic attitude angle data when rotated the low-cost IMU in different rotation directions. Fig.8 shows the dynamic attitude angle in roll direction and pitch direction. Because the IMU worked in random variable motion, we can see the dynamic curve measured by accelerometer is not stable, especially on the point when changing the motion direction. In a short time, the data drift from the gyroscope is not obvious. That is the reason why the dynamic curve measured by gyroscope is overlapped with the dynamic curve measured by sensor fusion method. However, the drift error will accumulate with time.



a) The angle in roll direction



b) The angle in pitch direction



b) The angle in pitch direction

Fig.8. Dynamic attitude angle from gyroscope, accelerometer and sensor fusion

From Fig.8, we know that the data from sensor fusion method not only inherits the little drift characteristics from accelerometer, but also inherit the transient stability from gyroscope. Here, we compared the performance of dynamic attitude angle estimation between this low-cost IMU used sensor fusion method and that pre-mentioned precise IMU. In order to get the high precise comparison result, we designed to make the low-cost IMU and the precise IMU in one same centre of gravity. Fig 9 shows this situation.

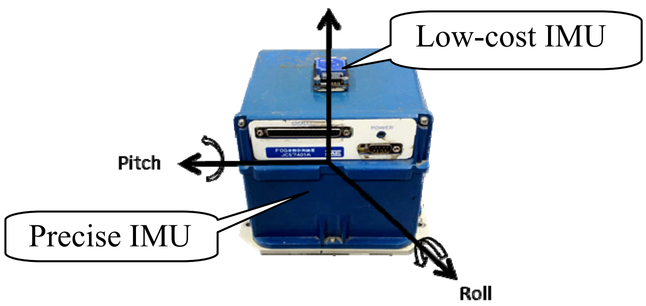
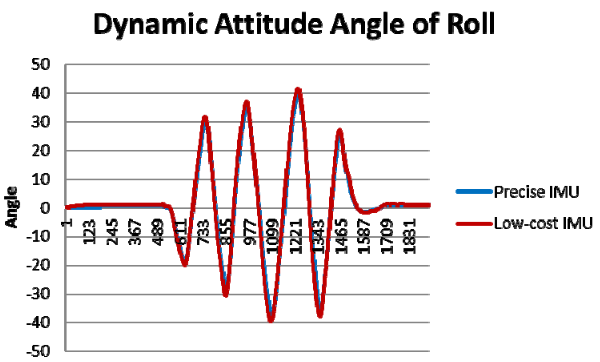


Fig. 9 The low-cost IMU and the precise IMU based comparison platform

Just as the approach used in comparing the dynamic angle estimation via gyroscope only, accelerometer only and sensor fusion method, we also rotate the low-cost IMU and the precise IMU together in different rotation directions and logged the data.



a) The angle in roll direction

Fig. 10. Dynamic attitude angle from the low-cost IMU and the precise IMU

Fig. 10 shows that the dynamic attitude angle of the low-cost IMU coincides with the precise IMU very well. It is concluded that a low-cost IMU has satisfactory performance of dynamic attitude angle estimation by using sensor fusion technology.

4. CONCLUSIONS

A sensor fusion technology combining low-pass filter with Kalman filter processed the data into attitude angle from a low-cost IMU for agricultural robot navigation. Based on this method, it compensated the IMU drift, improved the noise immunity and reduced the measurement error. At last, two parameters, drift error and dynamic attitude angle estimation, were chosen to compare with that of a precise IMU. The sensor fusion method is effective in attitude angle estimation.

REFERENCES

Chen Jengheng, Lee Souhen, Debra D B.(1994). Gyroscope free strapdown inertial measurement unit by six linear accelerometers. Journal of Guidance, Control and Dynamics,17(2),286-290.

IMU S4E5A0A0A1 Datasheet.(2011). SEIKO EPSON CORPORATION.

Mathieu St-Pierre, Denis Gingras Dr. Ing.(2004). Comparison between the unscented Kalman filter and the extended Kalman filter for the position estimation module of an integrated navigation information system. 2004 IEEE Intelligent Vehicles Symposium, 831-835.

Noguchi,N., Barawid,O.(2011). Robot farming system using multiple robot tractors in Japan agriculture. Preprints of the 18th IFAC World Congress Paper No.3838.