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Vehicle Dynamic State Estimation Using Smartphone Embedded Sensors

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Abstract: The access to the information on the vehicle motion state is of great significance for the vehicle stability control and the development of active safety products. However, the vehicle state parameter extraction is primarily accessed by attaching special sensors to the vehicles, which usually requires modification of redesign of the vehicle with high cost. Smartphone integrate gyro, orientation sensor, GPS and some other sensors thus providing a new way for vehicle dynamic parameter estimation. Therefore, we choose smartphone as our working platform, and data acquisition is fulfilled on a variety of mobile sensors embedded in an Android platform phone. Combining the features of these sensors and the properties of vehicle kinematics, a Kalman filter based sensor fusion approach is proposed to perform the vehicle state estimation. The parameters of vehicle heading angle and sideslip angle are extracted using fusion of data from the gyro, GPS and orientation sensor. Experiments carried on real vehicle show that the estimation results generated by fusing the gyro and orientation sensor are better than that of the gyro and GPS, but the two fusion approaches can complement each other in different contexts used. The main contribution of our work is that we provide a new attempt for accessing the vehicle dynamic parameters using off–the-shelf sensors. *Copyright © 2013 IFSA.*

Keywords: Vehicle dynamic state estimation, Smartphone, Kalman filter, Gyro, GPS, Orientation sensor.

1. Introduction

Knowledge of the vehicle dynamic state is essential to designing automotive control systems that increase safety and improve handling characteristics. Automotive active safety technologies, such as ABS, ESP, TCS, are heavily rely on the accurate estimation of the vehicle dynamic parameters including longitude and lateral velocity, acceleration, yaw rate, heading angle, sideslip angle and etc. [1]. Although some state parameters can be measured by vehicle-specific devices or sensors directly, the devices are usually expensive. Moreover, they require a specific installation and respective technical specifications are incompatible, which make it hard for production market but only for development and testing phase. How to use easy-to-deploy, low-cost sensors for vehicle state estimation is the main concern of this paper.

Currently, the achievements for the estimation of unknown vehicle parameters using known parameters are commonly base on multi-sensor data fusion techniques [2]. Because of the diversity and complexity of state parameters of the vehicle motion, to choose a suitable estimation algorithm to effectively integrate a variety of sensor data is the core issue of vehicle state estimation. Sasaki and Nishimaki use neural network method to estimate the vehicle sideslip angle [3]. The method creates a three-layer neural network to evaluate vehicle

dynamic performance, and the neural networks learning is gained by repeated real vehicle testing. Although this estimation method can achieve good results, the training process becomes very complicate for changes of the road and car conditions. The method for vehicle state estimation based on vehicle kinematics or vehicle dynamics using the Kalman filter has been widely used, covering the vehicle longitudinal speed, yaw rate, sideslip angle to the tire force estimation [4, 5]. Some researchers used high sampling rate GPS (Global Positioning System) or high-precision GPS/INS (Inertial Navigation System) integrated navigation system (e.g. RT 3000 (OXTS, 2008)) to predict the state of the vehicle and the kinematic (dynamic) model parameters [6, 7, 8]. These methods can estimate the vehicle state parameter accurately but the high-precision GPS and INS are too expensive that it's difficult to widely deploy them in practical applications. Smartphones integrate gyro, orientation sensor, GPS and some other sensors, providing a new way to acquire the vehicle state information. This paper attempts to use smartphone as the tool to achieve the vehicle state estimation.

The remainder of the paper is organized as follows: in section 2, the smartphone embedded sensors and the associated coordinate system are presented. Section 3 describes the vehicle kinematic model and the parameters need to be measured. The synthesis of the various sensor input is presented in section 4 where the Kalman filter based sensor fusion framework and the procedure of the state estimation are detailed. In section 5, experimental validation results are provided. Finally the paper is wrapped up with some conclusions and future works

2. Smartphone Embedded Sensors and Definition of Coordinate

Smartphones are usually configured with multiple accelerometers, orientation sensor, gyro and some other sensors. The sensor outputs on different directions have different definitions. The smartphone coordinate system (m frame) is shown in Fig. 1 (a). The coordinate origin is at the center of the touch screen, x-axis points to the right level, y-axis the front and z-axis the top. When the smartphone moves, the accelerometer can obtain three-axis acceleration components. The gyro outputs rotational angular velocities of the three axes. The orientation sensor can output azimuth angle which is the angle between projection of the y-axis on earth and the north direction of the earth.

Smartphones are also equipped with a GPS which can generate vehicle location and velocity information, corresponding to the navigation coordinate system (e frame). Depending on the geographical coordinates of the selected axis pointing in different order the navigation coordinate systems (e frame) can be divided into East North Up frame (ENU) and North East Dawn (NED) or other forms. ENU is used in the automotive industry ISO standard (ISO 8855), which is the coordinate system used in this paper. In addition, a vehicle can be regarded as a rigid body with mass and inertia, any movements of the vehicle will cause changes of its position and orientation, e.g. pitching or rolling. We can build a coordinate of the car body (b frame) by setting the center of gravity (cg) as the coordinate system origin O_b, the moving direction of the car O_bX_b, the horizontal axis of the vehicle point to the left side O_bY_b and above the vehicle O_bZ_b, as shown in Fig. 1 (b). ENU coordinate system is also marked. Putting the smartphone horizontally with the car, and making smartphone axis coincides with the axis of the vehicle, the vehicle parameters in different axes of motion of the vehicle itself can be obtained directly from the phone.

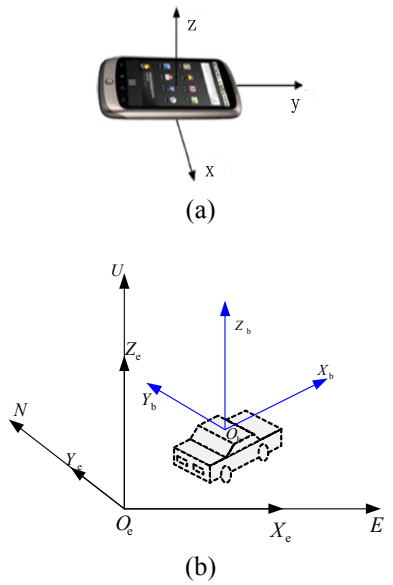


Fig. 1. Coordinate system definition:
(a) Coordinate of smartphone; (b) Navigation coordinate system and vehicle body coordinate system.

3. Vehicle Kinematic Modeling

Vehicle state estimation is closely related to the physical model of vehicle motion. According to the previous definition of the coordinate system, the establishment of vehicle motion model in the plane is shown in Fig. 2. The axes $X_eO_eY_e$ and $X_bO_bY_b$ constitute the horizontal planes of the navigation coordinate system and vehicle body coordinate system, respectively. Select the longitudinal axis pointing the moving direction of the car as X_b, the left side axis Y_b. The vehicle speed at the cg is denoted as V, $\dot{X}_b$ and $\dot{Y}_b$ are the velocity components on X_b and Y_b, respectively. $\dot{X}_e$ and $\dot{Y}_e$ are the east and north speed regarding to the navigation frame, respectively, which can be obtained by GPS.

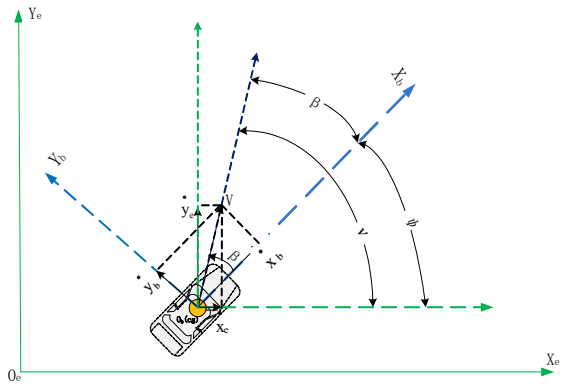


Fig. 2. Vehicle Kinematic Model.

Learning from the Fig. 2, we got the following relations between these velocity components:

$$V=\sqrt{\dot{X}_e^{\,2}+\dot{Y}_e^{\,2}}=\sqrt{\dot{X}_b^{\,2}+\dot{Y}_b^{\,2}} \tag{1}$$

Then, the track angle defined by the speeds in the two directions is:

$$\nu=\tan^{-1}(\dot{Y}_e/\dot{X}_e) \tag{2}$$

As the smartphone is closely attached to the vehicle body coordinate system, the yaw rate measured by the smartphone embedded inertial device, i.e. the gyro, can be regarded as the yaw rate of the vehicle body, which we denoted it ω_{gyro} here. It can be represented by the differential of vehicle heading angel (yaw angle) ψ :

$$\omega_{gyro}=\dot{\psi}+\varepsilon \tag{3}$$

where ε represents the gyro bias. Therefore, we can use this relationship to estimate the vehicle heading angle. The linear kinematic model of vehicle on the plane can be expressed by the following state equation:

$$\begin{bmatrix}\psi\\ \varepsilon\end{bmatrix}_{k+1}=\begin{bmatrix}1 & -T_s\\ 0 & 1\end{bmatrix}\begin{bmatrix}\psi\\ \varepsilon\end{bmatrix}_k+\begin{bmatrix}T_s\\ 0\end{bmatrix}\left[\omega_{gyro}\right]_k+\upsilon_k \tag{4}$$

where ψ and ε are the vehicle state parameters need to be estimated. ω_{gyro} is the output of gyro and υ_k is process-noise sequence. Considering the case of vehicle slipping, the motion at the vehicle cg (O_b) is not strictly coincide with the longitudinal direction X_b of the vehicle, but with a difference angle of β, which is defined as sideslip angle of vehicle [5]. As shown in Fig. 2, the relationship between the track angle ν, heading angel (yaw angle) ψ and sideslip angle β heading can be expressed by:

$$\beta = \nu - \psi \tag{5}$$

When the vehicle is moving in a straight line, the sideslip angle can be ignored. According to equation (2), we can approximate the heading angle ψ with the track angle ν measured by GPS, that is:

$$\left[\nu\right]_k=\begin{bmatrix}1 & 0\end{bmatrix}\begin{bmatrix}\psi\\ \varepsilon\end{bmatrix}_k+\omega_{GPS}, \tag{6}$$

where ω_{GPS} represents the GPS measurement noise. According to the previous definition, the azimuth output by direction sensor in smartphone denotes θ, which is the included angle between the longitudinal axis X_b of the vehicle and the North of ground. In this case, the vehicle heading angle ψ^{ref} measured by the orientation sensor in smartphone can be expressed as:

$$\psi^{ref} = 90 - \theta \tag{7}$$

Considering the measurement error in orientation sensor ω_{or}, the relation between measurement value ψ^{ref} and the state variables ψ, ε to be estimated is:

$$\left[\psi^{ref}\right]_k=\begin{bmatrix}1 & 0\end{bmatrix}\begin{bmatrix}\psi\\ \varepsilon\end{bmatrix}_k+\omega_{or} \tag{8}$$

4. Vehicle State Estimation Based on Kalman Filter

The Kalman Filter (KF) technique is very useful in the kinematic fusion process. The main reason for its success is that it has a very intuitively appealing state-space formulation and a predictor-corrector estimation and recursive-filtering structure. The recursive formulation can be simply summarized as: new estimate = previous estimate +gain times the residuals of the estimation [9]. This is a very powerful and yet simple estimation data-processing structure, especially for online and real-time application. The lineal KF usually deals with the state space model as follows:

$$\begin{cases}x(k+1)=A(k)x(k)+B(k)u(k)+\upsilon(k)\\ z(k)=H(k)x(k)+\omega(k)\end{cases} \tag{9}$$

where x is the $n\times1$ state vector; u is the control input vector to the dynamic system; z is the $m\times1$ measurement vector; υ is a white Gaussian process-noise sequence, with zero mean and covariance matrix Q; ω is a white Gaussian measurement-noise sequence, with zero mean and covariance matrix R; A is the $n\times n$ transition matrix that propagates the state x from k to $k+1$; B is the input matrix; H is the $m\times n$ measurement matrix. Kalman filter has two steps: the prediction step, where the next state of the system is predicted given the previous measurements, and the update step, where the current state of the

system is estimated given the measurement at that time step. The steps translate to equations as follows.

1) Predication:

$$\begin{cases} \tilde{x}(k+1|k) = A(k)\hat{x}(k|k) + B(k)u(k) \\ \tilde{P}(k+1|k) = A(k)\hat{P}(k|k)A(k)^T + Q(k) \end{cases} \quad (10)$$

2) Update:

$$\begin{cases} r(k+1) = z(k+1) - H(k+1)\tilde{x}(k+1|k) \\ S(k+1) = H(k+1)\tilde{P}(k+1|k)H(k+1)^T + R(k) \\ W(k+1) = \tilde{P}(k+1|k)H(k+1)^T S(k+1)^{-1} \\ \hat{x}(k+1|k+1) = \tilde{x}(k+1|k) + W(k+1)r(k+1) \\ \hat{P}(k+1|k+1) = \tilde{P}(k+1|k) - W(k+1)S(k+1)W(k+1)^T \end{cases} \quad (11)$$

where $\tilde{x}(k+1|k)$ and $\tilde{P}(k+1|k)$ are the predicted mean and covariance of the state, respectively, on the time step k+1 before seeing the measurement; $\hat{x}(k+1|k+1)$ and $\hat{P}(k+1|k+1)$ are the estimated mean and covariance of the state, respectively, on time step k+1 after seeing the measurement. $r(k+1)$ is the innovation or the measurement residual on time step k+1; $S(k+1)$ is the measurement prediction covariance on the time step k+1; $W(k+1)$ is the filter gain, which indicates how much the predictions should be corrected on time step k+1.

Based on the analysis of the last section, the estimated values of vehicle heading angle and sideslip angle can be achieved by data fusion of outputs of various types of sensors in smartphone. The state vector $x = [\psi \ \varepsilon]^{\mathrm{T}}$ to be estimated is constructed by the state equation of Kalman Filter formula (9) which can be derived by (4), the yaw rate ω_{gyro} measured by gyro is taken as the system input u . Combined with the measured outputs of GPS and orientation sensor, we can obtain two measurement equations, which are decided by formula (6) and (8). Thus, we can create two Kalman filters, KF-I and KF-II, respectively, to estimate the state parameters. The corresponding data fusion and state estimation process are shown in Fig. 3.

5. Experiment and Results

Field test with a passenger car is adopted, the road for test is 5 km long Peace Avenue in Wuhan, which is near the author's collage. Smartphone for the test is based on Android platform. Raw sensor data is obtained by using Android API function. It reports a new sample value whenever a change in sensor signal is detected, and the sampling rate is set to 15 Hz. To reduce the impact on measurement accuracy caused by the deployment of the smartphone , we fixed it to the gravity center of the car. And the Y axis of smartphone is coordinated with the moving direction of the car, Z axis with the roof of the car. At this time, the yaw rate of the car is exactly the rotate angle velocity of the smartphone with its Z axis. Meanwhile, to verify the effectiveness of the proposed method, we installed a high precision inertial navigation system (INS), namely RT2000. It integrates high precision gyroscope, accelerometer, magnetometer, GPS and other sensors. The measurement outputs of RT2000 can be set as calibration values to be used to make comparing with the estimation results of smartphone.

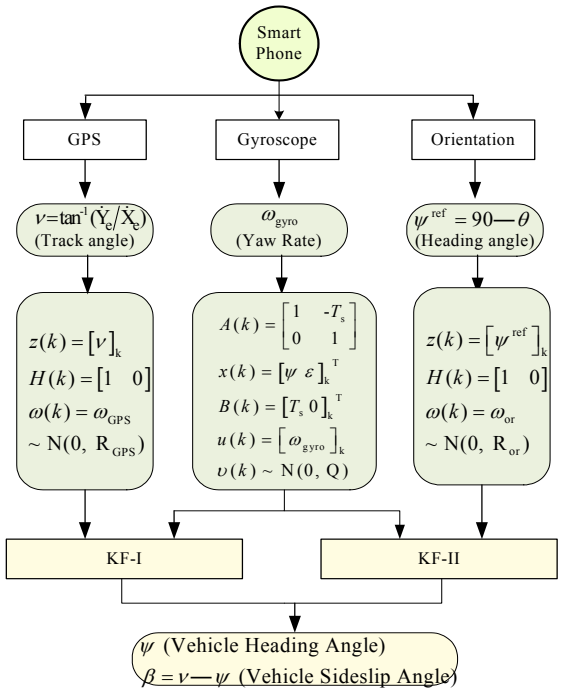


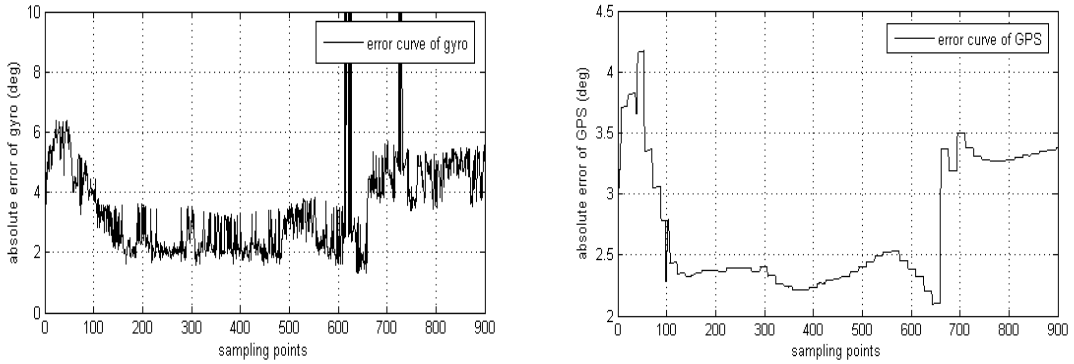
Fig. 3. The Procedure of Data Fusion and States Estimation.

In the test, KF-I implements data fusion of the outputs of gyro and GPS to extract an estimate value of the vehicle heading angle. The yaw angle is derived by integrating the yaw rate, which is provided by gyro. The track angle is provided by GPS. However, these two angle values can't be used directly as the heading angle, because of the inertial error of the sensors and slipping condition of the vehicle. We then compare these two values to the heading angle measured by high precision INS to calculate errors $e_1 = |X - X_1|$ and $e_2 = |X - X_2|$. Here X represents high-precision inertial measurement value, which can be used as the calibration reference value. X_1 is the yaw angle obtained by integrating outputs of gyro. X_2 is the track angle ν measured by GPS. e_1 and e_2 are the absolute error between the two angles and the outputs of the high-precision inertia system. The error performance of each sampling point is shown in Fig. 4 (a) and Fig. 4 (b). We can see that errors exist when calculating the vehicle heading angle by separately using the gyro and GPS in smartphone. Average each sampling points in

Fig. 4(a) and Fig. 4 (b), that is, $\overline{e}_1 = 1/n\sum_{i=1}^{n} e_{1,i}$ and $\overline{e}_2 = 1/n\sum_{i=1}^{n} e_{2,i}$ are the averaged errors of e_1 and e_2, respectively. The results are $\overline{e}_1 = 3.746$ and $\overline{e}_2 = 3.217$.

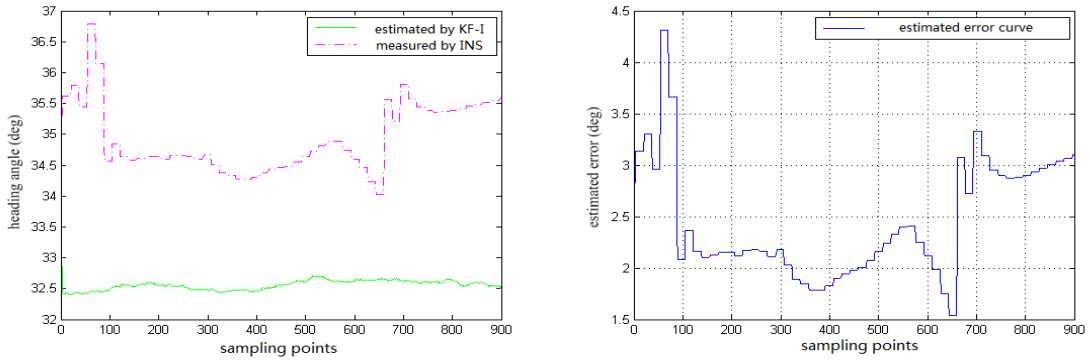
Using KF-I to implement data fusion for these two types of sensor, we can obtain the estimation of the vehicle heading angle. The result of comparing the estimated value and the heading angle measured by the INS is shown in Fig. 5 (a). In Fig. 5 (a), the solid line represents the estimated value generated by KF-I, and the dotted line represents the measured the value. Let X_3 be the estimated value by KF-I, then $e_3 = |X - X_3|$ is the absolute error of KF-I and INS. The corresponding error curve is shown in Fig. 5(b). Similarly, we calculate the averaged error $\overline{e}_3 = 1/n\sum_{i=1}^{n} e_{3,i} = 2.738$. It's evident that $\overline{e}_3 < \overline{e}_1$ and $\overline{e}_3 < \overline{e}_2$, which means the estimation accuracy of vehicle heading angle is improved after data fusion.

The target of KF-II is also to extract vehicle heading angle, but the objects of data fusion are the gyro and orientation sensor. Firstly, the error between the azimuth angle and the INS measured heading angle is observed, which is $e_4 = |X - X_4|$. X_4 is the azimuth ψ^{ref}. A similar calculation of averaged error of e_4 is $\overline{e}_4 = 1.186$. For reasons of space, we just present the error value while not drawing the error curves here.



(a) (b)

Fig. 4. Measurement error. (a) Absolute error of gyro (e_1). (b) Absolute error of GPS (e_2).



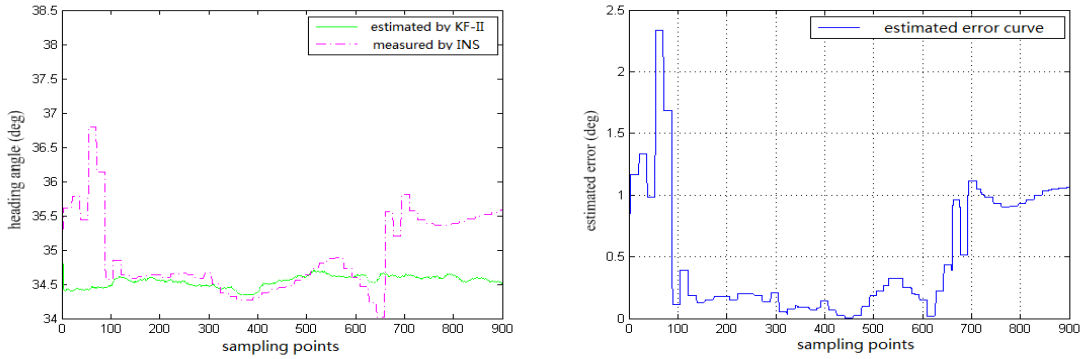
(a) (b)

Fig. 5. KF-I fusion results: (a) Estimated heading angle using KF-I: (b) Estimated error of KF-I (e_3).

After data fusion by KF-II, the extracted value of vehicle heading angle is shown in Fig. 6 (a), where the solid line is the curve of fusion results and the dotted line is the curve of measured heading angles using INS. Let X_5 be the estimated value of KF-II, then $e_5 = |X - X_5|$ is the absolute error between KF-II and INS. The corresponding error line is given in Fig. 6 (b). We can get $\overline{e}_5 = 0.692$. The heading angle accuracy has been improved after data fusion. Meanwhile, it's obvious that $\overline{e}_5$ is much smaller than $\overline{e}_3$, which means integration of gyroscope with orientation sensor in smartphone is better than that with GPS. Further analysis found that approximating the vehicle heading angle with track angle measured by GPS generates comparatively larger deviation because of the ignoring of the vehicle sideslip

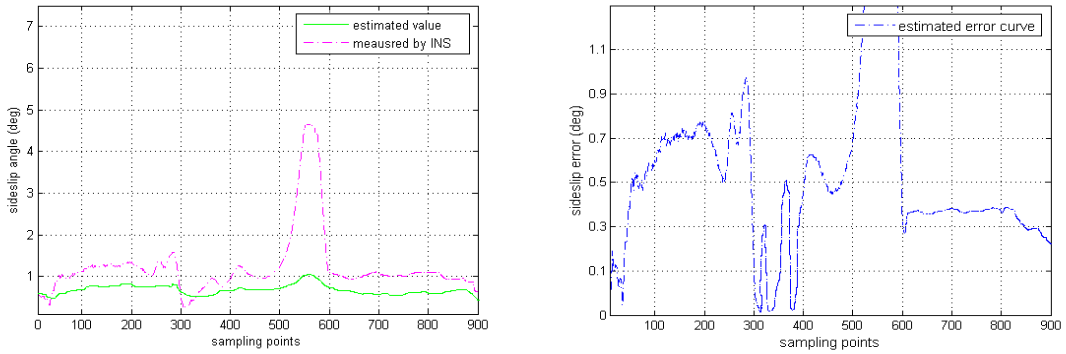
condition. While the output of the orientation sensor in smartphone is positioned closer to the heading angle, so the deviation is smaller.

Based on this, we adopt the heading angle generated by the data fusion of the orientation sensor and gyro to calculate vehicle sideslip angle. Taking the track angle ν and heading angle ψ into the equation (5), $\beta = \nu - \psi$, we will get the sideslip angle. The comparison of estimated sideslip angle by KF-II and that of INS is in Fig. 7 (a), and the absolute error curve is in Fig. 7 (b). The averaged value of the errors is $\overline{e}_6 = 0.652$, which in a reasonable range. So we conclude that adopting orientation sensor and gyro for calculation of the vehicle heading angle and sideslip angle leads to more better performances.



(a) (b)

Fig. 6. KF-II fusion results: (a) Estimated heading angle using KF-II, (b) Estimated error of KF-II (e_5).



(b) (b)

Fig. 7. Estimated sideslip angle: (a) Estimated sideslip angle value; (b) Estimated error (e_6).

6. Conclusions

Vehicle dynamic state information is the basis of vehicle handling stability study and automotive active safety system. In this paper, smartphone is adopted as the tool for obtaining vehicle state information. Based on the analysis of vehicle kinematic model, the vehicle state model is determined. The data fusion method for smartphone gyro, GPS and orientation sensor is devised by Kalman filter, extracting the vehicle heading angle and sideslip angle. Real vehicle tests show that the extracted results obtained by integrating smartphone gyro and orientation are better than integrating gyro and GPS. However, they can complement each other in practical scenarios. In a magnetic field environment with strong interference, the orientation sensor will generate a great deviation. In this condition, using GPS and gyro for estimating the state parameters is better. The next step is to introduce more smartphone sensors, like accelerometer, to improve extracting accuracy of vehicle state. Moreover, we can use the state information in smartphones to carry out researches on vehicle driving monitoring and warning or some other related applications.

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