Vehicle Sideslip and Roll Parameter Estimation using GPS

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This paper demonstrates a method for obtaining estimates of key vehicle states using the Global Positioning System (GPS) and Inertial Navigation System (INS) sensor measurements. A Kalman filter integrates the INS sensors with GPS to provide high update estimates of the sensor biases, heading, and vehicle velocities, which can be used to calculate the vehicle slip angle. Since the INS sensors and GPS antennas are attached to the vehicle body, roll and pitch effects from the vehicle motion and road influence the measurements obtained from the sensors and GPS. This paper develops a method that incorporates these roll and pitch effects to improve the accuracy of the vehicle state and sensor bias estimates. With accurate measurements of roll angle and roll rate, it is also possible to estimate key roll parameters, such as roll stiffness and damping ratio, with a second order dynamic model. Comparison of the vehicle state estimates with those predicted by the theoretical vehicle model yields similar results. This similarity verifies that the estimation scheme is giving appropriate estimates of the states.

Keywords / Sideslip, Slip Angle, Longitudinal Velocity, Parameter, Vehicle, Estimation, Roll, GPS

1. INTRODUCTION

The ability to accurately measure or estimate vehicle sideslip and absolute longitudinal velocity is a critical determinant in the performance of many vehicle control systems such as braking control, stability control and lateral control systems [1,2]. In emergency situations, sideslip is necessary to detect a sliding or skidding vehicle, which may have normal yaw rates. Also in these situations, the absolute vehicle velocity cannot be accurately measured by wheel speed because of excessive wheel slip. Both sideslip and absolute velocity are necessary in determining the vehicle's behavior in such situations.

However, these values are not directly measured on production cars and therefore must be estimated instead. Two common techniques for estimating these values are to integrate inertial sensors directly and to use a physical vehicle model [3,4]. Some methods use a combination or switch between these two methods appropriately based on vehicle states [1,4]. Direct integration methods can accumulate sensor errors and unwanted measurements from road grade and superelevation (side-slope). In addition, methods based on a physical vehicle model can be sensitive to changes in the vehicle parameters and are only reliable in the linear region.

Bevly and others proposed a method to estimate vehicle sideslip and absolute longitudinal velocity using the Global Positioning System (GPS) and Inertial Navigation System (INS) sensors which avoids these estimation errors [5,6]. The estimation method is based on a planar vehicle model with single antenna GPS setup. However, out-of-plane vehicle motions due to roll and pitch cannot be taken into account with the planar vehicle model and can lead to false vehicle state estimates. In addition, heading estimates from simple gyro integration can be corrupted by an unknown sensor bias.

This paper presents a new method to estimate vehicle sideslip angle, longitudinal velocity, and attitude using GPS measurements from a two-antenna system combined with INS sensors. INS sensors are integrated with GPS measurements to provide higher update estimates of the vehicle states because the update rate of common GPS receivers, which is usually 1~10 Hz, is not high enough for control purposes. A two-antenna GPS receiver with antennas placed laterally provides the ability to determine the vehicle's attitude, roll and yaw, and eliminates errors due to gyro integration. Vehicle sideslip can be estimated by the difference between the vehicle heading and the direction of vehicle velocity because a GPS receiver provides an absolute velocity of the vehicle.

This paper also investigates the influence of road grade, superelevation, and vehicle roll on the GPS-based vehicle sideslip and longitudinal velocity estimation. A new method is proposed to compensate for these effects when estimating vehicle sideslip. While the road grade can be estimated by examining the ratio of vertical velocity to horizontal velocity from a single-antenna GPS receiver because the longitudinal motion of the vehicle dominates over the lateral motion [7], a two-antenna GPS receiver is required to measure the road superelevation. Knowledge of road superelevation and vehicle roll (or tolerance to their effects) are also necessary in lateral and stability control systems because they directly influence both the vehicle lateral dynamics and lateral acceleration measurements [8].

Experimental results of the sideslip estimation from the new scheme and the earlier approach without the compensation are compared with predicted values from a validated bicycle model. The results provide evidence that the scheme can correct for changes in grade and roll. In addition to the sideslip and longitudinal measurements, roll and yaw of the vehicle, gyro bias, accelerometer bias, and corrected acceleration are also available from the proposed method.

In addition, the laterally placed GPS antennas suggest a distinctive way to estimate parameters related to vehicle roll dynamics. These parameters could be used, for instance, in rollover warning [9] or active suspension systems. It is shown that the roll-related parameters - roll stiffness and damping - can be accurately estimated using GPS and INS measurements.

2. PLANAR BICYCLE MODEL AND SIDESLIP

The bicycle model shown in Figure 1 is a 2 DOF vehicle model in a plane with lateral velocity and yaw rate as the states. The lateral and yaw motions are described in Equation (1).

$$\begin{bmatrix} \dot{u}_{y,CG} \\ \dot{r} \end{bmatrix} = \begin{bmatrix} \frac{-C_{\alpha f}-C_{\alpha r}}{m u_{x,CG}} & -u_{x,CG} + \left(\frac{C_{\alpha r} b - C_{\alpha f} a}{m u_{x,CG}}\right) \\ \frac{C_{\alpha r} b - C_{\alpha f} a}{I_z u_{x,CG}} & \frac{-C_{\alpha f} a^2 - C_{\alpha r} b^2}{I_z u_{x,CG}} \end{bmatrix} \begin{bmatrix} u_{y,CG} \\ r \end{bmatrix} + \begin{bmatrix} \frac{C_{\alpha f}}{m} \\ \frac{C_{\alpha f} a}{I_z} \end{bmatrix} \delta \quad (1)$$

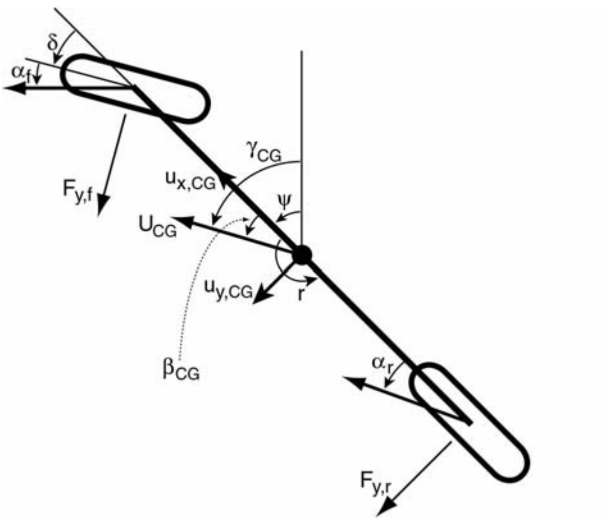

Fig. 1 Bicycle Model

Given longitudinal and lateral velocity, u_x and u_y, at any point on the vehicle body, the sideslip angle can be defined by:

$$\beta = \tan^{-1}\left(\frac{u_y}{u_x}\right) \quad (2)$$

The sideslip angle at the center of gravity (CG) is shown by β_{CG} in Figure 1. The sideslip angle can also be defined by the difference between the vehicle heading (ψ) and the direction of the velocity (γ) at any point on the body.

$$\beta = \gamma - \psi \quad (3)$$

Since a two-antenna GPS receiver provides both velocity and attitude measurements, the vehicle heading and direction of velocity can be directly measured and the sideslip angle can be calculated using Equation (3).

3. GPS/INS INTEGRATION BY KALMAN FILTER

INS sensors are integrated with GPS measurements to provide higher update rate estimates of the vehicle states because the update rate of common GPS receiver is not high enough for control purposes [6]. The vehicle states could be estimated from the physical model in Equation (1) but it is valid only in the linear region and uncertainties in the vehicle parameters and sensor biases may result in significant estimation errors. Therefore, a kinematic model, which is independent of physical parameters, is used to estimate the vehicle states and several Kalman filters are applied to estimate the sensor biases and integrate the GPS measurements with INS sensors.

The traditional Kalman filter is comprised of a measurement update and time update. Because of the lower update rate of the GPS measurement, the measurement update is performed only when GPS is available in order to estimate the sensor bias and zero out the state estimate error. The measurement update is generally described by:

$$\begin{aligned} & x_+(t) = x_-(t) + K\left[y(t) - Cx_-(t)\right] \\ & K = P_-(t)C^T\left[CP_-(t)C^T + R\right]^{-1} \quad or \quad K = P_+(t)C^T R^{-1} \\ & P_+(t) = \left[I - KC\right]P_-(t) \quad or \quad P_+(t)^{-1} = P_-(t)^{-1} + C^T R^{-1} C \end{aligned} \quad (4)$$

where:

$x_-(t)$ = prior estimate of the system state at time t
$x_+(t)$ = updated estimate of the system state at time t
$P_-(t)$ = prior error covariance matrix at time t
$P_+(t)$ = updated error covariance matrix state at time t
K = Kalman Gain
$y(t)$ = new measurement
C = observation matrix
R = measurement noise covariance

x and y represent vehicle states of interest and available measurements, respectively, for a general filter. Simple integration of the INS sensors is performed during the time update because GPS measurements are not available. The time update can be written as:

$$\begin{aligned} & x_-(t+1) = x_+(t) + \Delta t \cdot \dot{x}_+(t) \\ & P_-(t+1) = A_d P_+(t) A_d^T + Q \end{aligned} \quad (5)$$

where:

A_d = discretized system dynamics matrix
$= I + \Delta t \cdot A$ (using Euler method)
Q = process noise covariance

This Kalman filter structure is used throughout the paper for estimating various vehicle states and sensor biases.

4. STATE ESTIMATION WITH PLANAR MODEL

Following on earlier work [6], INS sensors are integrated with GPS measurements to estimate vehicle states. In the previous approach, the vehicle heading is estimated by integrating a yaw gyro. However, this estimate is problematic since the gyro bias cannot be known exactly. Therefore, two separate Kalman filters are constructed by utilizing a two-antenna GPS receiver to improve the previous work. One estimates vehicle heading (yaw) to eliminate errors arising from gyro integration and the other estimates absolute longitudinal and lateral velocities of the vehicle without using wheel speed.

For the yaw Kalman filter, the kinematic relationship between yaw rate measurements and yaw angle can be written as:

$$r_m = \dot{\psi} + r_{bias} + noise \tag{6}$$

where:

ψ = yaw angle (vehicle heading)

r_m, r_{bias} = yaw rate gyro measurement and bias

The yaw angle can be measured using a two-antenna GPS receiver.

$$\psi_m^{GPS} = \psi + noise \tag{7}$$

where:

ψ_m^{GPS} = yaw angle measurement from GPS

A linear dynamic system can be constructed from Equation (6) and (7) using the INS sensors as the input and GPS as the measurement.

$$\begin{bmatrix} \dot{\psi} \\ \dot{r}_{bias} \end{bmatrix} = \begin{bmatrix} 0 & -1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \psi \\ r_{bias} \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} r_m + noise \tag{8}$$

When GPS attitude measurements are available,

$$\psi_m^{GPS} = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} \psi \\ r_{bias} \end{bmatrix} + noise \tag{9}$$

The Kalman filter in Equations (4) and (5) is then applied to the system to estimate the vehicle heading and the gyro bias. State vector x in the Kalman filter is $[\psi \;\; r_{bias}]^T$, which are yaw angle of the vehicle and yaw rate gyro bias, respectively. The measurement y in the Kalman filter is the yaw angle from GPS, ψ_m^{GPS}, with observation matrix C, which is [1 0] only when GPS measurements are available. Observation matrix C is [0 0] when GPS measurements are not available.

For the velocity Kalman filter, the kinematic relationship between acceleration measurements and velocity components at the point where the sensor is located can be written as:

$$\begin{aligned} a_{x,m} &= \dot{u}_{x,sensor} - \dot{\psi} \cdot u_{y,sensor} + a_{x,bias} + noise \\ a_{y,m} &= \dot{u}_{y,sensor} + \dot{\psi} \cdot u_{x,sensor} + a_{y,bias} + noise \end{aligned} \tag{10}$$

where:

$u_{x,sensor}$ = longitudinal velocity at sensor location

$a_{x,m}, a_{x,bias}$ = longitudinal accelerometer measurement and bias

$u_{y,sensor}$ = lateral velocity at sensor location

$a_{y,m}, a_{y,bias}$ = lateral accelerometer measurement and bias

The longitudinal and lateral velocity can be measured using GPS velocity along with the yaw Kalman filter. First, the sideslip angle (β^{GPS}) needs to be calculated using the velocity vector (U^{GPS}) from the GPS measurement and the vehicle heading (ψ) from the yaw Kalman filter by Equation (3). Then, the longitudinal velocity measurement ($u_{x,m}^{GPS}$) and lateral velocity measurement ($u_{y,m}^{GPS}$) are simply by:

$$\begin{aligned} u_{x,m}^{GPS} &= \left\| U^{GPS} \right\| \cdot \cos(\beta^{GPS}) \\ u_{y,m}^{GPS} &= \left\| U^{GPS} \right\| \cdot \sin(\beta^{GPS}) \end{aligned} \tag{11}$$

Assuming the primary GPS antenna that gives velocity measurements is placed right above the sensor location, the measured velocity components from GPS can be written as:

$$\begin{aligned} u_{x,m}^{GPS} &= u_{x,sensor} + noise \\ u_{y,m}^{GPS} &= u_{y,sensor} + noise \end{aligned} \tag{12}$$

where:

$u_{x,m}^{GPS}$ = longitudinal velocity measurement from GPS

$u_{y,m}^{GPS}$ = lateral velocity measurement from GPS

Note that Equation (12) holds only when the primary GPS antenna is located above the sensor location. If not, an additional velocity term from yaw rate must be taken into account.

A Kalman filter is then applied to the following linear dynamic system from Equation (10) and (12) to estimate the vehicle velocities and the sensor biases.

$$\begin{bmatrix} \dot{u}_{x,sensor} \\ \dot{a}_{x,bias} \\ \dot{u}_{y,sensor} \\ \dot{a}_{y,bias} \end{bmatrix} = \begin{bmatrix} 0 & -1 & r & 0 \\ 0 & 0 & 0 & 0 \\ -r & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} u_{x,sensor} \\ a_{x,bias} \\ u_{y,sensor} \\ a_{x,bias} \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} a_{x,m} \\ a_{y,m} \end{bmatrix} + noise \tag{13}$$

where:

$$r = \dot{\psi} = r_m - r_{bias} = \text{compensated yaw rate}$$

When GPS velocity measurements are available,

$$\begin{bmatrix} u_{x,m}^{GPS} \\ u_{y,m}^{GPS} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} u_{x,sensor} \\ a_{x,bias} \\ u_{y,sensor} \\ a_{x,bias} \end{bmatrix} + noise \tag{14}$$

In the Kalman filter of Equations (4) and (5), state vector x is $[u_{x,sensor} \;\; a_{x,bias} \;\; u_{y,sensor} \;\; a_{y,bias}]^T$ and measurement y is $[u_{x,m}^{GPS} \;\; u_{y,m}^{GPS}]^T$.

5. EXPERIMENTAL RESULTS - PLANAR MODEL

A Mercedes E-class wagon is used for the experiment. The test vehicle is equipped with a 3-axis accelerometer/rate gyro triad sampled at 100 Hz. Sensor noise levels (1σ) are 0.06 m/s^2 for the accelerometers and 0.2 deg/s for the rate gyros. The vehicle is also equipped with Novatel GPS antenna/receiver pairs providing 10 Hz velocity measurements and 5 Hz attitude measurements with a noise level (1σ) of less than 3 cm/s and 0.2 deg respectively.

Because the GPS receiver introduces a half sample period inherent latency and a finite amount of time is needed in computation and data transfer, the time tags in the GPS measurement messages and the synchronizing pulse from the receiver are used to align the GPS information with the INS sensor measurements. This synchronizing process is very important when the INS sensors are combined with the GPS measurements because any time offset between two measurements may result in significant estimation errors [6].

Figure 2 shows heading angle estimates compared to measurements. Experimental tests consisting of several laps around an uneven parking lot are performed. Note that integration of INS sensors fills in the gaps between GPS measurements. The combination of GPS measurements with INS measurements provides 100 Hz updates of the vehicle state.

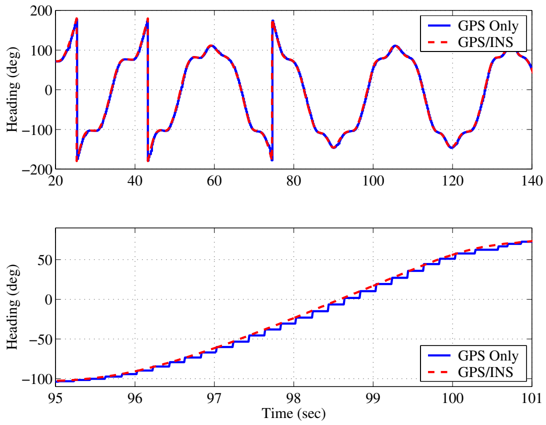

Fig. 2 Heading Angle Estimates

Yaw rate and sideslip angle estimates from the GPS/INS integration compared with the bicycle model are shown in Figure 3. Since the velocity Kalman filter estimates the velocity at the sensor location, the velocity estimates are translated to the center of gravity with yaw rate for comparison with the bicycle model. The similarity between estimated and model yaw rates demonstrates that the bicycle model used in the comparison is valid and calibrated.

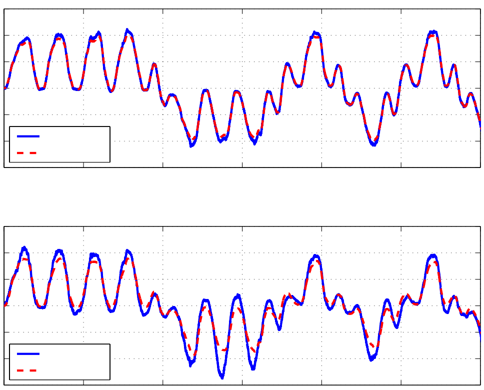

Fig. 3 Yaw Rate and Sideslip Angle Estimates

However, it is interesting to note that there are differences between estimated and modeled sideslip angles. It is found that these differences are consistent with the uneven grade and superelevation of the test path. The correlation between the differences and unevenness of the surface can be easily seen by comparing the accelerometer biases with the surface grade and vehicle roll.

The surface grade can be estimated by examining the ratio of vertical velocity to horizontal velocity from the GPS measurement because the longitudinal motion of vehicle dominates over the lateral motion [7].

$$\theta_r \approx \tan^{-1}\left(\frac{U_V}{U_H}\right) \qquad (15)$$

where:

θ_r = road grade estimate
U_V, U_H = vertical and horizontal velocity from GPS

Figure 4 shows the comparison of longitudinal accelerometer bias and grade estimate using filtered GPS velocities.

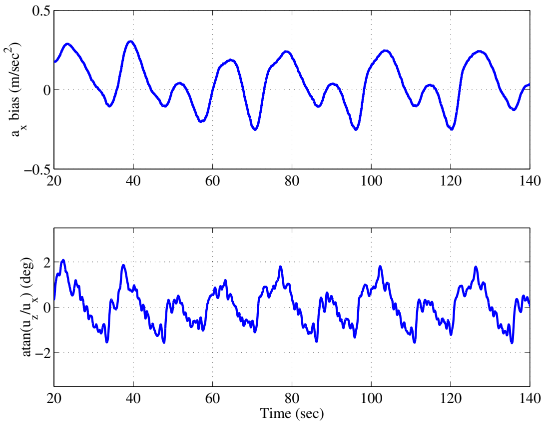

Fig. 4 Longitudinal Accelerometer Bias and Grade Estimate

It is clearly seen that the there is a strong correlation between longitudinal accelerometer bias and the grade along the test path. Similarly, the lateral accelerometer bias follows the roll. The comparison of lateral accelerometer bias and roll angle measurement is shown in Figure 5. Since the two antennas of the GPS receiver are placed laterally, the combination of road superelevation (road side-slope) and vehicle roll can be directly measured.

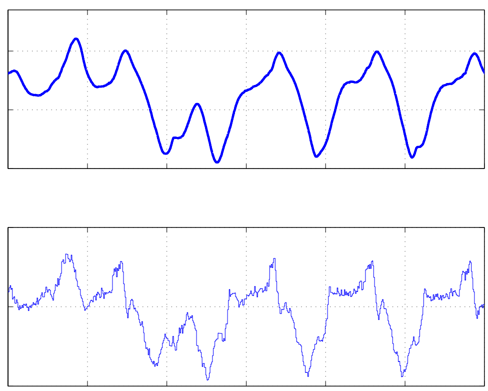

Fig. 5 Lateral Accelerometer Bias and Roll Angle

Unlike the gyro measurement, the accelerometer measurement will contain a gravity component due to vehicle roll and pitch in addition to true vehicle acceleration. These undesired components from gravity degrade the performance of the velocity Kalman filter.

Even so, the estimated sideslip is still much better than that obtained from simply integrating the accelerometer [6].

6. ROLL CENTER MODEL WITH ROAD GRADE

Due to vehicle roll and pitch, the accelerometer measures the desired acceleration along with a gravity component. However, the gravity component in the acceleration measurement can be compensated if the roll and pitch experienced by the vehicle are known. In order to fully determine the vehicle's attitude, a three-axis gyro and three-antenna GPS receiver, which is uncommon and hard to calibrate, are necessary. However, assuming vehicle pitch is caused mostly by road grade, which can be estimated by examining the velocity ratio using Equation (15), gravity components in acceleration measurements due to roll and pitch can be compensated using only a two-antenna GPS receiver.

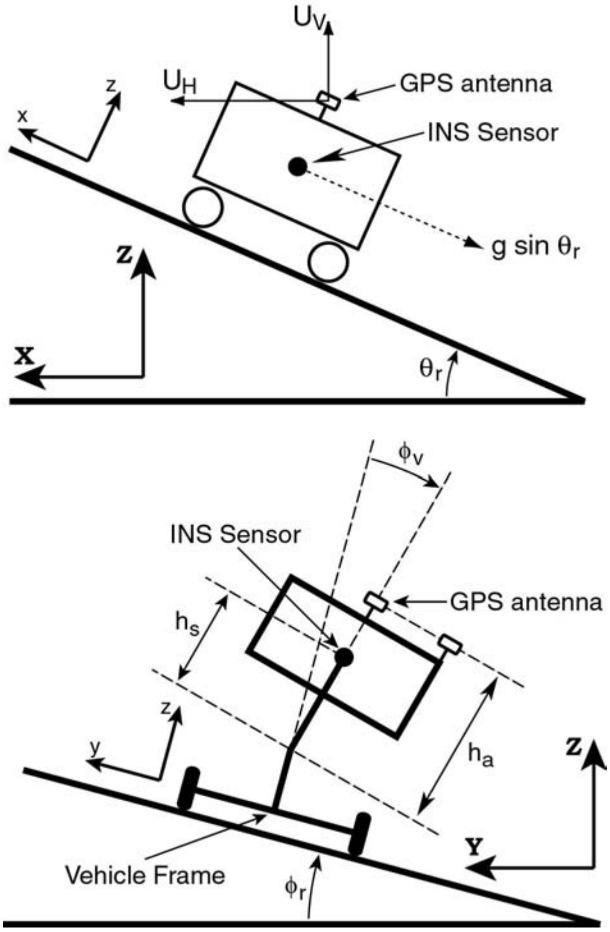

Fig. 6 Roll Center Model with Grade and Superelevation

A roll center vehicle model with road grade and superelevation is shown in Figure 6. This model assumes the vehicle body rotates about a fixed point (the roll center) on a frame that remains in the plane of the road. Since the grade of the surface can be estimated from the GPS velocity measurement and vehicle roll including the superelevation of the surface can be measured utilizing the two-antenna GPS receiver, the expected gravity component in the acceleration measurement can be explicitly specified and compensated in Equation (10).

The kinematic relationship between acceleration measurements and velocity components at the sensor location for this model can be written as:

$$\begin{aligned} a_{x,m} &= \dot{u}_{x,sensor} - \dot{\psi} \cdot u_{y,sensor} + a_{x,bias} + g \cdot \sin\theta_r + noise \\ a_{y,m} &= \dot{u}_{y,sensor} + \dot{\psi} \cdot u_{x,sensor} + a_{y,bias} + g \cdot \sin\phi_t + noise \end{aligned} \quad (16)$$

where:

θ_r = road grade estimate

$\phi_t = \phi_r + \phi_v$ = sum of road superelevation and vehicle roll

A Kalman filter is then applied as before using Equation (16).

Another important advantage in using the roll center model is that the roll motion of vehicle can be taken into account. Note that Equation (16) is written for the point at which the sensor is located and the two GPS antennas are placed on the top of the vehicle roof. Therefore, there is an additional velocity component due to vehicle roll in the GPS velocity measurement and this additional velocity component should be compensated. This can be done by translating the velocity at the antenna to the point at which the sensor is located using Equation (17).

$$\begin{aligned} u_{x,m}^{GPS} &= u_{x,sensor} + noise \\ u_{y,m}^{GPS} &= u_{y,sensor} - p \cdot (h_a - h_s) + noise \end{aligned} \quad (17)$$

where:

p = roll rate

h_a = distance from roll center to GPS antenna

h_s = distance from roll center to INS sensor

This roll rate compensation plays an important role when the vehicle is experiencing a heavy roll motion. If the primary GPS antenna is not placed right above the INS sensor, a yaw rate of the vehicle should be taken into account.

In addition, the sum of road superelevation and vehicle roll can be estimated by constructing a roll Kalman filter in the same manner as in the yaw Kalman filter. Since the GPS antennas and roll gyro are attached to the vehicle body, only the sum of road superelevation and vehicle roll angle can be estimated.

For the roll Kalman filter, the kinematic relationship between roll rate measurements and roll angle can be written as:

$$p_m = \dot{\phi}_t + p_{bias} + noise \quad (18)$$

where:

p_m, p_{bias} = roll rate gyro measurement and bias

The roll angle can be measured using a two-antenna GPS receiver.

$$\phi_m^{GPS} = \phi_t + noise \quad (19)$$

where:

ϕ_m^{GPS} = roll angle measurement from GPS

The roll Kalman filter is then implemented using Equation (18) and (19) in the same manner as in the yaw Kalman filter. The state vector x is $[\phi_t \;\; p_{bias}]^T$ and the measurement y is the roll angle from GPS, ϕ_m^{GPS}.

7. EXPERIMENTAL RESULTS - ROLL MODEL

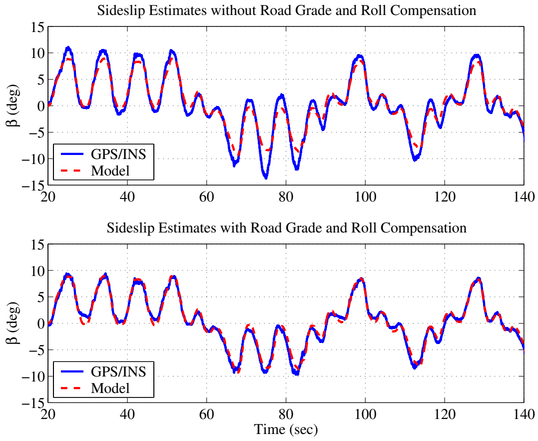

Fig. 7 Comparison of Sideslip Angle Estimates

Figure 7 shows the experimental results of sideslip angle estimation with and without the compensation. Since the velocity Kalman filter estimates the velocity at the sensor location, whereas the bicycle model generates the sideslip angle at the center of gravity, the velocity estimates from the filter are translated with yaw and roll rates to the fixed frame for the comparison with the bicycle model. Note that the discrepancies between the model and estimate are significantly reduced after the compensation. The same improvement can be seen in the case of longitudinal velocity estimation shown in Figure 8. Any difference between the longitudinal velocity estimate and wheel speed after the compensation is most likely due to longitudinal slip of the tire.

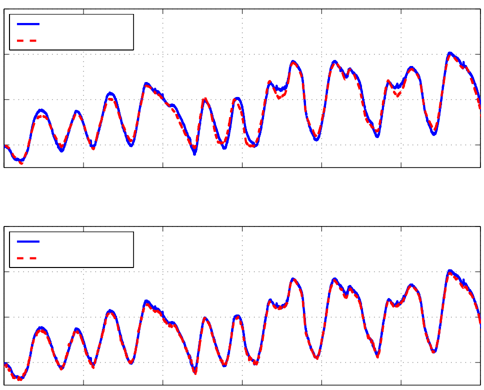

Fig. 8 Longitudinal Velocity Estimates

The combination of road superelevation and vehicle roll angle is also estimated from the roll Kalman filter. Figure 9 shows roll estimates together with GPS roll measurements. Integration of INS sensors fills in the gaps between GPS measurements giving a smooth roll signal.

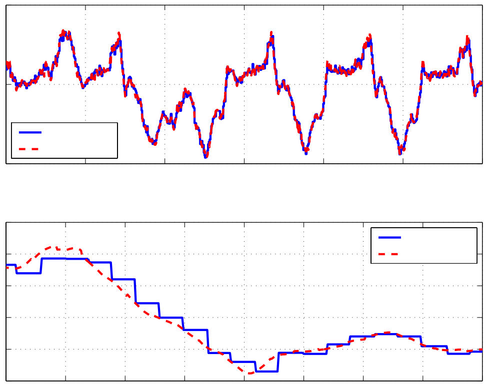

Fig. 9 Roll Angle Estimates

With accurate measurements of roll angle and roll rate, it is possible to estimate parameters related to the roll dynamics such as roll stiffness and damping ratio. A dynamic roll model can be used for a wide variety of applications including rollover warning [9] or active suspension. In addition, a parameterized vehicle roll dynamic model could conceivably be used to separate roll and superelevation.

8. ROLL PARAMETER ESTIMATION

In order to consider vehicle roll dynamics, the related parameters have to be estimated first. The two-antenna GPS setup with INS sensors suggests a distinctive way to estimate parameters related to vehicle roll dynamics as well as to estimate vehicle sideslip.

The following linear second order model (spring-damper-mass system) is used for the estimation [10].

$$I_{xx} \cdot \ddot{\phi}_v + b \cdot \dot{\phi}_v + k \cdot \phi_v = m \cdot a_y \cdot h + m \cdot g \cdot h \cdot \phi_v \qquad (20)$$

where:

I_{xx}, b, k = roll moment of inertia, damping ratio, and stiffness

m = vehicle mass

h = distance between roll center and center of mass

The roll angle, roll rate, and lateral acceleration can be measured from the GPS receiver and INS sensors. Because the roll acceleration is not directly available, numerical differentiation of the roll rate is used to get the roll acceleration. The roll moment of inertia, damping ratio, and stiffness can be estimated using a least squares estimator.

Since the roll measurements include the road superelevation as well as the vehicle roll, experimental runs should be performed with enough length of time and test path to average out the contribution from road superelevation changes.

9. ROLL PARAMETER ESTIMATION RESULTS

The roll stiffness and damping ratio are estimated by exciting the vehicle roll dynamics. An approximated value for the roll moment of inertia [11] is used because normal driving does not create enough excitation to accurately identify the moment of inertia. In order to minimize the interference from road superelevation changes, several experimental runs are performed on a fairly flat surface. The estimated roll stiffness and damping ratio are shown in Figure 10. The least squares fit is shown as a line going through the data points.

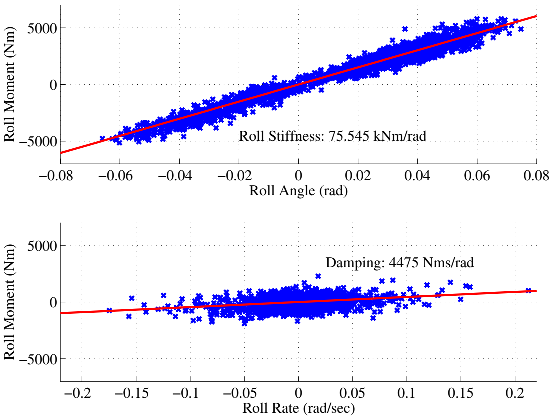

Fig. 10 Roll Moment of Inertia and Damping Ratio Estimates

To compare the result, the roll stiffness is also estimated by performing a series of constant radius turns at constant speed. The vehicle will experience different roll angles with various speeds since the lateral acceleration will be varying along with the speeds. Figure 11 shows the plot of roll angle vs. lateral acceleration as well as the estimated roll stiffness. A line going through the data points represents the least squares best fit of the roll rate.

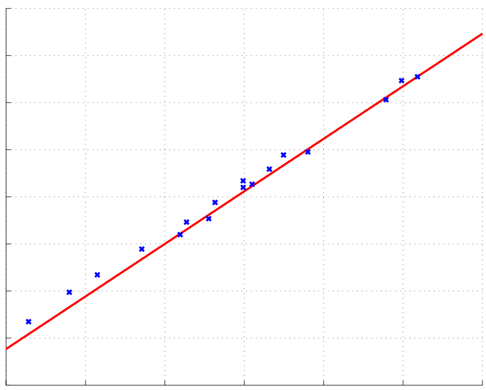

Fig. 11 Plot of Roll Angle vs. Lateral Acceleration

The estimated roll stiffness from the constant speed turns is very similar to the roll stiffness estimated in Figure 10. The difference between two roll stiffness estimates is less than 5%.

In addition, several step steer maneuvers are performed to validate the estimation result. Figure 12 and 13 show the measured roll angle and roll rate as well as the simulated values using estimated parameters.

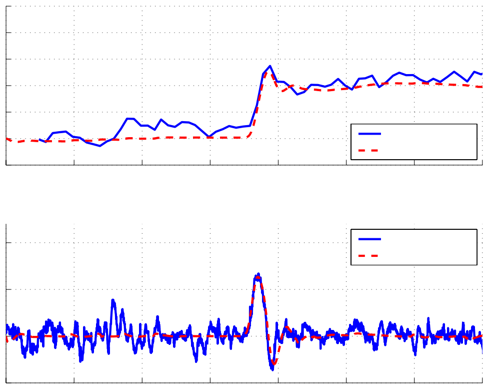

Fig. 12 Comparison of Step Steer Response

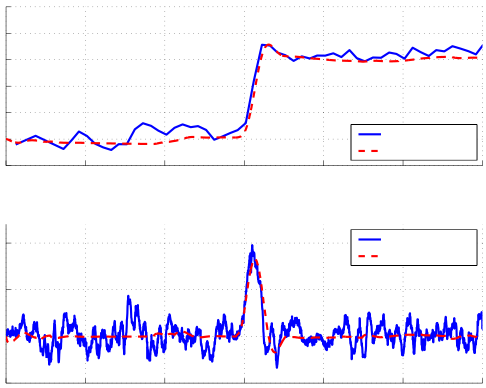

Fig. 13 Comparison of Step Steer Response

It is clearly seen that major response characteristics such as rise time, overshoot, and steady state value are well matched between the measured and simulated roll angle and rate. The noisy differences between the two values are most likely caused by unevenness of the test path since the road is not simulated. The slight discrepancies in the roll rate comparisons, especially after the peaks, can be explained by nonlinear damping characteristic.

10. CONCLUSION

In this paper, it is shown that the roll and grade corrected vehicle states and roll parameters can be estimated using a two-antenna GPS receiver combined with INS sensors. The proposed method is shown to provide accurate high update estimates of the vehicle states, including sideslip and longitudinal velocity. As a future step, the obtained sideslip and longitudinal velocity can be used to estimate the tire cornering and longitudinal stiffness. The obtained vehicle states will be used for implementing steer-by-wire control and driver assistance system.

11. ACKNOWLEDGMENTS

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