Vehicle Speed Estimation Using GPS/RISS (Reduced Inertial Sensor System)

Thomas O'Kane and John V. Ringwood

Department of Electronic Engineering
National University of Ireland, Maynooth, (NUIM), Maynooth, Co. Kildare
E-mail: tom.okane@eeng.nuim.ie, john.ringwood@eeng.nuim.ie

Abstract — **Land vehicle speed is usually measured by wheel speed or GPS. While these methods are adequate for some purposes, there are some drawbacks. Wheel speed may differ greatly from vehicle speed due to tyre slip. In addition, speed measured by GPS contains little high frequency information and lags the actual vehicle speed. A method is needed which combines both accuracy and good transient behaviour. This paper describes a method that combines GPS and a Reduced Inertial Sensor System (RISS), in this case a single accelerometer, to achieve an accurate estimate of vehicle speed. Using a Kalman filter, the low frequency accuracy of the GPS and high frequency response of the accelerometer are combined. A number of error correction strategies are applied to provide a robust and accurate measurement system.**

Keywords — **Kalman filter, estimation, GPS, RISS, INS, vehicle**

I Introduction

Inertial Navigation Systems (INS) use inertial sensors to determine the position, velocity and orientation of a vehicle. An Inertial Measurement Unit (IMU) consists of three accelerometers and three gyros mounted orthogonally, and may be combined with a Global Positioning System (GPS) receiver to form a GPS/INS system [1]. Reduced Inertial Measurement Systems (RISS) [2] use a sub-set of the inertial sensors. Tightly coupled systems [3], which combine raw GPS and INS data in a single state estimator give the best performance but are more expensive and less accessible than loosely coupled systems. In loosely coupled systems, INS data is combined with the data output from the GPS state estimator. These systems offer acceptable accuracy for many applications [4].

Although Micro-Electro-Mechanical Systems (MEMS) technology has reduced INS cost and weight considerably, for some applications a full GPS/INS system may not be justified on the grounds of cost, weight or complexity. This paper presents a low cost single purpose system to measure vehicle speed in the direction of travel, more accurately than GPS alone. A single longitudinally-mounted accelerometer is used to augment GPS data in a loosely coupled GPS/RISS system. The system is intended for use in testing competition motorcycles, where weight is a factor.

II System overview

The system is shown in Fig. 1. The accelerometer is sampled at a much higher rate than the GPS so two models are used, one using data from both sensors when available, and the other using accelerometer data alone when a new GPS sample is unavailable. A separate Kalman filter is applied to each model and these are labelled "KF1 INS/GPS" and "KF INS" respectively. The INS Kalman filter continues to provide vehicle speed updates if the GPS signal is lost.

As shown in the accelerometer signal path in Fig. 1, the accelerometer data may be multiplied by a calibration constant, and compensation is applied for acceleration-induced vehicle pitch. The dashed outlines enclose two error compensation systems. Drift compensation cancels any offset on the accelerometer measurement. GPS error compensation detects any difference between GPS and accelerometer data and adjusts the weighting of sensor measurements in the Kalman filter. These error correction mechanisms are treated in more detail in Section VI.

III Measurement characteristics

GPS and accelerometer data are measured. Accelerometer sample rates from 100 to 800 samples per second were tested and the sample rate chosen was 400 samples per second. A GPS receiver with an update rate of 12.5 per second was used. By combining GPS and accelerometer data, the strengths of both sensors are exploited; the good low frequency and steady state accuracy of the GPS and the good high frequency response of the accelerometer.

a) *Accelerometer data*

Accelerometer data, when integrated, provides high frequency information about vehicle speed but there are some problems. Due to engine and road vibration, the signal is noisy. Any offset on the accelerometer output creates drift when integrated.

b) *GPS data*

GPS data does not give a good instantaneous measurement of vehicle speed. The sample rate is low and it lags the actual vehicle speed. The GPS signal is sometimes lost when blocked by terrain. However, the low frequency accuracy is good.

A measurement is available of the number of satellites visible to the GPS receiver. A threshold is applied, below which the the GPS speed signal is considered invalid and accelerometer data alone is used. For simplicity, this measurement is not shown in Fig. 1, but it can be seen in some data plots, for example Fig. 5.

IV Measurement model

The continuous time system, input and measurement matrices are A, B and C respectively. The discrete time state transition matrix, input and measurement matrices are F, G and H respectively.

a) *The accelerometer model*

The accelerometer is modelled as an integrator as shown in equation (1), where x_1 and x_2 are vehicle speed and acceleration respectively and T is the sample period.

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{k+1} = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_k \tag{1}$$

b) *The GPS model*

The GPS model is shown in equation (2), where x_3 and x_4 are the vehicle speed and acceleration respectively as measured by the GPS.

$$\begin{bmatrix} x_3 \\ x_4 \end{bmatrix}_{k+1} = \begin{bmatrix} F_{11} & F_{12} \\ F_{21} & F_{22} \end{bmatrix} \begin{bmatrix} x_3 \\ x_4 \end{bmatrix}_k + \begin{bmatrix} G_1 \\ G_2 \end{bmatrix} x_{1_k} \tag{2}$$

The input is vehicle speed, x_1. A continuous time GPS model was found from recorded data using Matlab's System Identification Toolbox. The continuous time system matrices were found to be:

$$A = \begin{bmatrix} 0 & 1 \\ -1427.2 & -114.2 \end{bmatrix} \tag{3}$$

and

$$B = \begin{bmatrix} 0 \\ 1427.2 \end{bmatrix} \tag{4}$$

The discrete time matrices F and G are then calculated for the appropriate sample rate.

c) *The combined accelerometer and GPS model*

Combining the two models described by equations (1) and (2) gives:

$$X_{k+1} = FX_k \tag{5}$$

where

$$X = \begin{bmatrix} x_1 & x_2 & x_3 & x_4 \end{bmatrix}^T \tag{6}$$

and

$$F = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ G_1 & 0 & F_{11} & F_{12} \\ G_2 & 0 & F_{21} & F_{22} \end{bmatrix} \tag{7}$$

F is the state transition matrix for the combined model.

$$y_k = HX_k \tag{8}$$

where

$$H = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{9}$$

States x_2 (actual acceleration) and x_3 (GPS speed) are being measured.

As explained in Section II, a separate model is used when only accelerometer data is available. It is derived from the combined model above, by redefining the measurement matrix H.

$$H = \begin{bmatrix} 0 & 1 & 0 & 0 \end{bmatrix} \tag{10}$$

The state vector X and transition matrix F are common to both models. The essential difference between the models is in what is being measured.

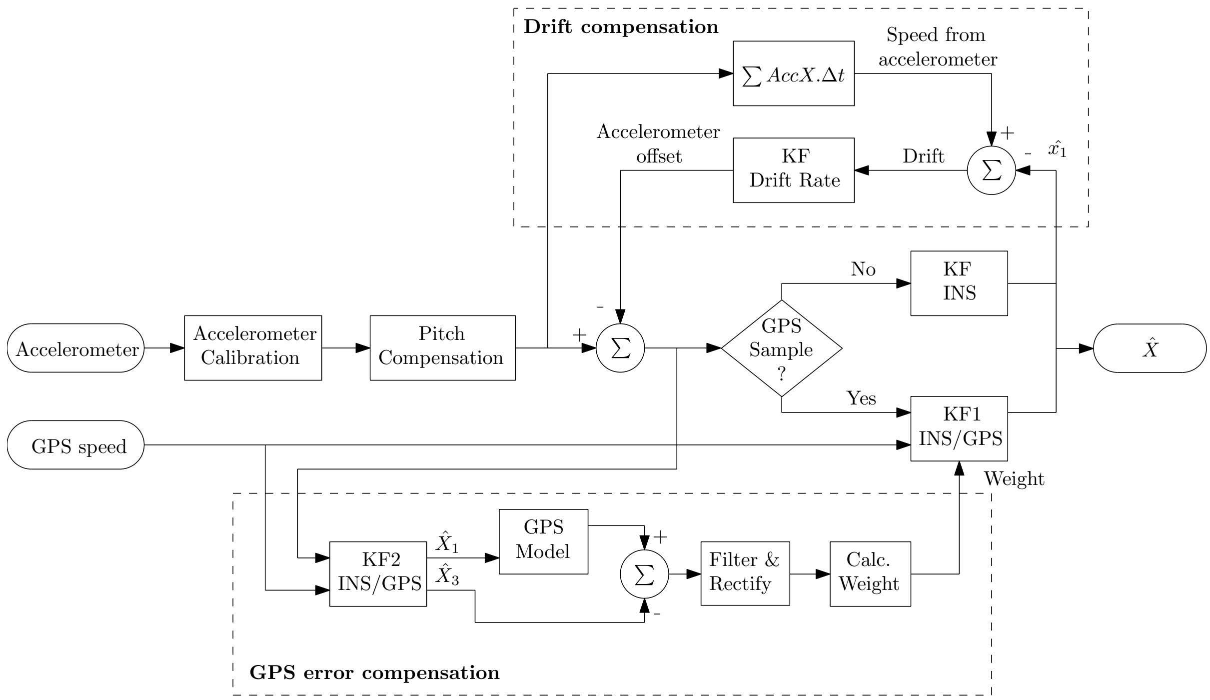

Fig. 1: System diagram

V Signal estimation

A separate Kalman filter operates on each of the two models. The noise model parameters were found empirically using recorded data and Kalman filter gains for both were calculated off-line. The state vector estimate $\hat{X}$ is calculated by one or other Kalman filter, depending on whether or not a GPS sample is available.

a) INS/GPS covariance matrix specification

The process noise covariance matrix is:

$$P = \begin{bmatrix} 5 & 0 & 0 & 0 \\ 0 & 4 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{11}$$

and the measurement noise covariance matrix is:

$$R = \begin{bmatrix} 3.5 & 0 \\ 0 & R_{22} \end{bmatrix} \tag{12}$$

where

$$R_{22} = 72E + 40 \tag{13}$$

E is the GPS speed error. As the error varies from 0 to 5, R_{22} varies from 40 to 400. Kalman filter gains were calculated off-line for values of R_{22} in this range and the matrix elements were parameterised as functions of R_{22}. When the system is running, R_{22} is calculated from the GPS speed error and is then used to calculate the Kalman filter gain.

b) INS covariance matrix specification

The process noise covariance matrix is the same as for the INS/GPS Kalman filter, but the measurement noise $R = 0.4$. R is a scalar because the only measurement is the accelerometer. It has a lower value than in the INS/GPS Kalman filter because it is the only measurement and is being weighted more heavily relative to the process noise.

VI Error correction

a) Vehicle pitch

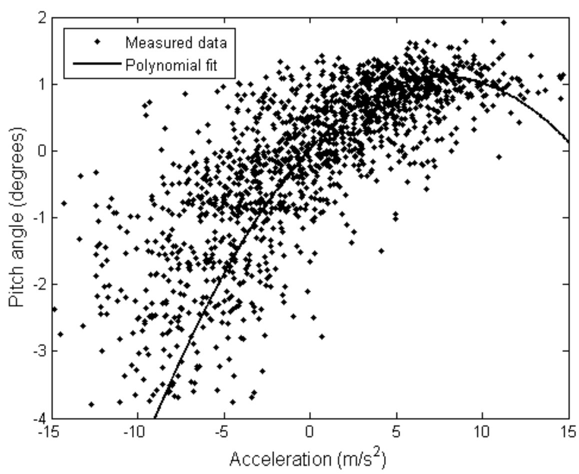

Fig. 2: Pitch angle vs. acceleration and polynomial fit.

The accelerometer is nominally aligned with the longitudinal axis of the vehicle, which is assumed to be the direction of travel, and any deviation of the accelerometer from this direction introduces an error [5]. The attitude of the accelerometer varies due to acceleration-induced pitch. This effect is negligible on cars but is more pronounced on motorcycles. Fig. 2 is a plot of motorcycle pitch angle versus acceleration, and a polynomial which was fitted to the data.

$$pitch = -0.0183a^2 + 0.2822a + 0.0207 \tag{14}$$

where a is acceleration. For motorcycles, three methods of handling pitch were considered; ignoring pitch altogether, calculating the pitch angle accurately using suspension travel measurements, and using the polynomial to calculate the approximate pitch angle from measured acceleration. Compared to calculating it from suspension position, ignoring the pitch angle gave a maximum error of approximately $0.28m/s$. Calculating the approximate pitch angle from acceleration using the fitted polynomial gave a maximum error of approximately $0.07m/s$. Measuring suspension positions requires extra hardware and complexity so it was decided to use the approximate value given by the curve fit.

b) Speed drift correction

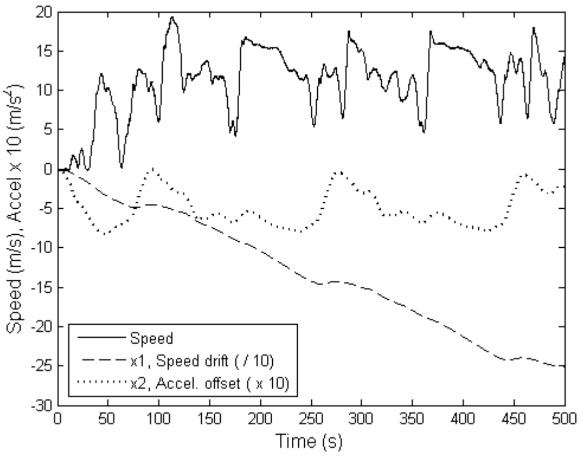

Fig. 3: Acceleration offset and speed drift.

Any offset on the accelerometer measurement causes drift when the signal is integrated to get speed. A constant offset may exist due to bad sensor calibration. If the vehicle is travelling up or downhill, an offset exists due to gravity. Measured acceleration, a is

$$a = A + g\sin\theta \tag{15}$$

where A is the vehicle acceleration, g is acceleration due to gravity and θ is the angle of the slope. While this offset is not constant, it changes slowly with time.

The drift in vehicle speed is the difference between the vehicle speed output ($\hat{x_1}$) and integrated acceleration. During the intervals between GPS samples, vehicle speed is estimated using accelerometer data alone. Therefore, if left uncompensated, the effect of drift is most noticeable when the GPS signal is lost for some time and the system is completely dependent on accelerometer data.

A separate Kalman filter is used to track the speed drift and estimate the accelerometer offset that gives rise to it. The model is again an integrator:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{k+1} = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_k \tag{16}$$

with the states x_1 and x_2 being speed and acceleration respectively.

$$H = \begin{bmatrix} 1 & 0 \end{bmatrix} \tag{17}$$

The output of interest is state x_2, the accelerometer offset. This offset is subtracted from the accelerometer measurement.

Fig. 3 shows the signals of the system states. The Kalman filter gain was tuned so as to give an acceptable compromise between rise time and steady state performance. The data was recorded in a car, driven repeatedly around a short hilly course. In Fig. 3, the acceleration offset is multiplied by 10, so in fact the accelerometer has an offset of approximately $-0.5m/s^2$.

c) GPS error

The GPS receiver provides an output of the number of visible satellites. When this number falls below a set threshold, the GPS speed data is disregarded. However, even with a high number of visible satellites, GPS data may be incorrect. This may occur when a satellite which forms part of the GPS receivers current solution becomes invisible. The receiver adopts another solution and the GPS estimate of position may change abruptly [6]. This in turn gives rise to velocity and acceleration errors.

In the combined model described in Section IV, states x_1 and x_3 represent speed as seen by the accelerometer and GPS respectively. By taking the difference between these states, a measure of disagreement between the two sensors can be found. This is done using the Kalman filter labelled “KF2 INS/GPS” in Fig. 1. Simply subtracting one state from the other would result in differences which are due to the GPS phase lag, so x_1 is passed through the GPS model to predict the expected value for x_3, given x_1. The difference between this value and x_3 is the measure of GPS speed error. Given that the accelerometer is a simpler sensor than the

GPS, it is assumed that the difference arises due to GPS error. As explained in Section V, the difference is used to weight the Kalman filter gain away from the GPS and towards the accelerometer.

Kalman filter "KF2 INS/GPS" has the same process noise covariance matrix as "KF1 INS/GPS" (Eqn. 11) and a fixed measurement noise covariance matrix

$$R = \begin{bmatrix} 3.5 & 0 \\ 0 & 40 \end{bmatrix} \tag{18}$$

so the calculation of GPS speed error is not affected by changes to the weighting of the measurements.

VII Results

a) Estimated speed compared to GPS speed

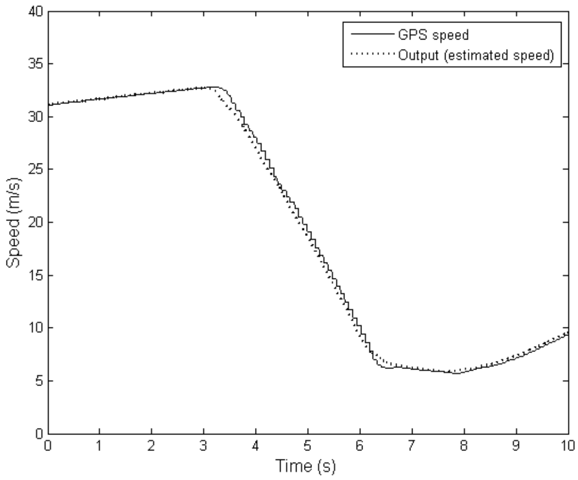

Fig. 4: Braking and acceleration.

Fig. 4 shows a number of characteristics of the estimated vehicle speed $\hat{x_1}$. From time 0 to 3 seconds, the car is accelerating; from 3 to 6 seconds, it is braking and from 8 seconds on it is accelerating again. From 0 to 3 seconds, the estimated speed is close to the GPS speed. It can be seen that the algorithm exploits the low frequency accuracy of the GPS speed measurement. During the braking period, the lag in the GPS signal can be seen and the slow update rate of the GPS speed is clear. When braking ends, the GPS speed data overshoots. When the car begins moderate acceleration at 8 seconds, the lag in the GPS speed can be seen again.

b) Loss of GPS signal

An important aspect of the system is its ability to estimate vehicle speed when no GPS signal is available or when not enough satellites are visible to provide the required accuracy. This may be caused by terrain, and in the case of a two wheeled

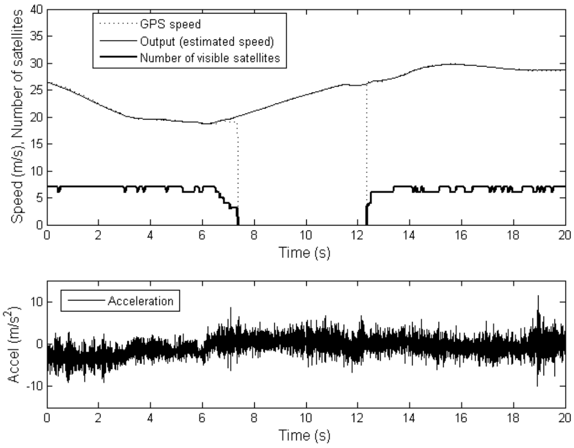

Fig. 5: Loss of GPS signal in tunnel and accelerometer signal.

vehicle, satellites may become invisible to the receiver due to lean angle [7]. Fig. 5 shows the car travelling through a tunnel where the GPS signal is lost for approximately five seconds. During this time, the GPS speed and number of visible satellites drop to zero. GPS data is used only when seven or more satellites are visible to the receiver. On entering the tunnel, the car accelerates at a steady rate. Just before 12 seconds, the car stops accelerating. This can be seen on both the estimated speed and accelerometer data. When the satellites become visible at the tunnel exit, the GPS speed returns with a small overshoot. The estimated speed matches the GPS speed and does not need any correction.

c) GPS error

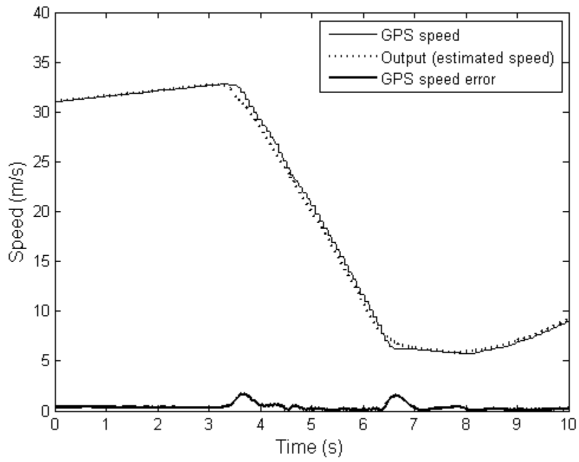

Fig. 6: Speed difference between accelerometer and GPS.

As described in Section VI, the disagreement in measured speed between the accelerometer and GPS is calculated. Fig. 6 shows this signal. The value increases in places where the GPS signal overshoots. In these places, the weighting in the

Kalman filter is shifted away from the GPS measurement and towards the accelerometer.

VIII Conclusion

This paper has shown a basic integration method between GPS and a Reduced Inertial Sensor System, which provides a more accurate estimate of vehicle speed than GPS alone. It incorporates correction for the main sources of error and handles short GPS outages such as when the GPS signal is blocked by terrain. As a loosely coupled system, it is easily accessible to vehicle or tyre manufacturers, who require an accurate vehicle speed measurement.

IX Acknowledgements

This research was generously assisted by 2D Datarecording, Karlsruhe, Germany, (http://2d-datarecording.com/) who provided the data recorder, GPS hardware, sensors and data recording software. This support is gratefully acknowledged.

References

[1] R. M. Rogers, *Applied Mathematics in Integrated Navigation Systems*. American Institute of Aeronautics and Astronautics, 2007.

[2] U. Iqbal, A. F. Okou, and A. Noureldin, "An integrated reduced inertial sensor system - riss / gps for land vehicle," (Monterey, CA, United states), pp. 1014 – 1021, 2008.

[3] J. Georgy, A. Noureldin, Z. Syed, and C. Goodall, "Nonlinear filtering for tightly coupled riss/gps integration," (Indian Wells, CA, United states), pp. 1014 – 1021, 2010.

[4] L. N. Hieu and V. H. Nguyen, "Loosely coupled gps/ins integration with kalman filtering for land vehicle applications," in *Control, Automation and Information Sciences (ICCAIS), 2012 International Conference on*, pp. 90–95, 2012.

[5] A. Brandt and J. Gardner, "Constrained navigation algorithms for strapdown inertial navigation systems with reduced set of sensors," in *American Control Conference, 1998. Proceedings of the 1998*, vol. 3, pp. 1848–1852 vol.3, 1998.

[6] Trimble Navigation Ltd., "How GPS Works: A Tutorial." http://www.trimble.com/gps_tutorial/, 2013. [Online; accessed 9-April-2013].

[7] M. Hayashi, T. Tanaka, and M. Yonekawa, "High accuracy positioning of two-wheeled vehicle at high speed traveling using gps," in *SICE Annual Conference, 2008*, pp. 3500–3503, 2008.