INVESTIGATING DIFFERENT VEHICLE VELOCITY ESTIMATORS AND AN ADAPTIVE KALMAN FILTER FOR ANTI-LOCK BRAKING SYSTEMS FOR OFF-ROAD VEHICLES

Alexander E. Berndt[a], Wietsche C. W. Penny[a] and P. Schalk Els[a]

[a]*Vehicle Dynamics Group – Dept. of Mechanical and Aeronautical Engineering – University of Pretoria – Private Bag X20, Hatfield, 0028– RSA*
berndtae@gmail.com, wietsche.penny@gmail.com, schalk.els@up.ac.za

Abstract

Vehicle velocity is a critical parameter for ABS systems since the wheel slip is determined from this metric and is a direct input for most ABS algorithms. An adaptive Kalman filter is proposed to increase the accuracy of the vehicle's velocity estimation, especially on rough terrains. The Kalman filter is compared to a non-linear estimator and a maximum wheel speed estimator on Belgian paving. An experimental setup is described which is used to evaluate the performance of the three estimators and to validate the Kalman filter's performance. Finally, a theoretical analysis is done regarding the effect each estimator has on a vehicle's ABS braking performance.

Keywords: velocity estimation, ABS algorithm, Kalman filter, off-road braking

1. Introduction

Anti-lock Braking System (ABS) algorithms, such as the Bosch ABS algorithm (Bauer and Bosch, 1999), typically use wheel slip and wheel acceleration to determine whether or not a wheel is locking up and adjust the calliper pressure accordingly. Since vehicle velocity cannot be measured directly, it needs to be estimated in order to determine the wheel slip for each wheel. The accuracy of this estimate is critical since if the wheel slip incorrectly determined, the vehicle's braking performance will be compromised.

ABS braking on rough terrain poses significant problems, among which are the tyre dynamics, vertical load variation and the estimation of vehicle velocity (Hamersma and Els, 2014). In particular, the estimation of vehicle velocity may degrade because of a number of contributing factors such as the wheel encountering undulations and the change of the effective rolling radius.

A VBox 3i unit was used in this study as a baseline to which various velocity estimators could be compared. When the VBox Global Positioning System (GPS) is coupled with a base station (DGPS), it allows for velocity measurements accurate to 0.1 km/h (Racelogic, 2017). However, such a system is expensive and thus poses an interesting problem, as vehicle velocity on most commercial vehicles is not measured directly, but rather have to be estimated from wheel speed sensor and accelerometer measurements.

Various complexity levels of velocity estimation can be implemented, ranging from non-linear estimators (Penny and Els, 2016), adaptive estimators (Jiang and Gao, 2000) to the more advanced Kalman filter designs (Amiri and Bijan, 2012). As previously mentioned, the rough terrain input may lead to wheel speed fluctuation and might strain the estimator that will lead to severe errors in the computation of longitudinal slip. A robust, accurate estimator with as few inputs as necessary is required to ensure accurate slip calculation. Three different velocity estimators will be used in this study with the Bosch algorithm to evaluate the effect of velocity estimation accuracy has on ABS performance.

This paper delves into different estimators, with varying complexity, as well as proposing an adaptive Kalman filter to determine the vehicle velocity. These estimators' performance is analysed by comparing them to the vehicle's actual velocity as measured by the VBox 3i DGPS system.

2. Estimators and Algorithms

To estimate vehicle velocity, three different estimators were used. Each estimator builds on the previous one, increasing in complexity as well as theoretical accuracy.

2.1 Maximum Wheel Speed Estimator

A simple method to estimate the vehicle velocity is by taking the maximum wheel velocity as the vehicle velocity. The reason behind this approach is that, during ABS braking, it is highly unlikely that all four wheels lock up at the same time, implying that at least one wheel accurately represents the true vehicle velocity. The problem with this estimator is that if all four wheels were to lock up, the vehicle velocity would be largely inaccurate.

2.2 Non-Linear Estimator

The non-linear (NL) estimator is adapted from the work by Penny and Els (2016). This estimator takes the fastest wheel speed and uses it as the vehicle velocity. However, if the highest wheel speed decelerates faster than a prescribed limit $\boldsymbol{R}$, the wheel is assumed to be locking and the estimated vehicle velocity is calculated based on this deceleration limit. The equations describing the motion are described in Eq. 1 and 2.

$$\dot{y}(t) = -R\ \mathrm{sat}\big(y(t) - x(t)\big), \qquad y(t = 0) = y_0 \tag{1}$$

$$\mathrm{sat}(x, d) = \begin{cases} -1, & x < -d \\ 1, & x > d \\ \dfrac{x}{d}, & -d < x < d \end{cases} \tag{2}$$

where $\mathrm{y(t)}$ is the vehicle velocity and $\mathrm{x(t)}$ the maximum wheel speed. Note that $\dot{y}(t)$ is limited by R, which is selected to represent the maximum possible deceleration of the vehicle on a certain road surface. R is predetermined and is given a value which depends on the surface that the vehicle is expected to drive on. This estimator is non-adaptive, meaning that if the estimator were optimised for asphalt (with a high R value), but the vehicle were to drive on a slippery surface such as ice, or very loose gravel, the vehicle's maximum deceleration would be far less and the estimator would render an underestimated vehicle velocity.

2.3 Proposed Adaptive Kalman Filter

The adaptive Kalman filter addresses the main issue of the NL estimator by directly measuring the vehicle's deceleration using an accelerometer. This allows the vehicle velocity estimation to be adapted depending on the surface the vehicle is driving on. Equations 3 through 9 define the Kalman filter's working principles.

The predict equations state that:

$$\hat{\boldsymbol{x}}_{k|k-1} = \boldsymbol{F}_k \hat{\boldsymbol{x}}_{k-1|k-1} + \boldsymbol{B}_k \boldsymbol{u}_k \tag{3}$$

$$\boldsymbol{P}_{k|k-1} = \boldsymbol{F}_k \boldsymbol{P}_{k-1|k-1} \boldsymbol{F}_k^T + \boldsymbol{B}_k \boldsymbol{Q}_{inputs} \boldsymbol{B}_k^T + \boldsymbol{Q}_k \tag{4}$$

The prediction is updated using the following equations:

$$\tilde{\boldsymbol{y}}_k = \boldsymbol{z}_k - \boldsymbol{H}_k \hat{\boldsymbol{x}}_{k|k-1} \tag{5}$$

$$\boldsymbol{S}_k = \boldsymbol{H}_k \boldsymbol{P}_{k|k-1} \boldsymbol{H}_k^T + \boldsymbol{R}_k \tag{6}$$

$$\boldsymbol{K}_k = \boldsymbol{P}_{k|k-1} \boldsymbol{H}_k^T \boldsymbol{S}_k^{-1} \tag{7}$$

$$\hat{\boldsymbol{x}}_{k|k} = \hat{\boldsymbol{x}}_{k|k-1} + \boldsymbol{K}_k \tilde{\boldsymbol{y}}_k \tag{8}$$

$$\boldsymbol{P}_{k|k} = (\boldsymbol{I} - \boldsymbol{K}_k \boldsymbol{H}_k) \boldsymbol{P}_{k|k-1} \tag{9}$$

The state variable $\hat{\boldsymbol{x}}_{k|k}$ comprises of an estimated vehicle velocity v (using the NL estimator described in Section 2.2) and the accelerometer bias a_b. The accelerometer bias is based on the random walk model and used to eliminate accelerometer drift. The input variable $\boldsymbol{u}_k$ contains the vehicle acceleration measurement a. Equations 10 and 11 are used to determine $\boldsymbol{F}_k$ and $\boldsymbol{B}_k$.

$$\boldsymbol{v}_{k|k-1} = \boldsymbol{v}_{k-1|k-1} + \Delta t \left(a_k - a_{b_{k-1|k-1}} \right) \tag{10}$$

$$a_{b_{k|k-1}} = a_{b_{k-1|k-1}} \tag{11}$$

The process noise covariance matrix **Q** is determined as the combination of Q_k and Q_{inputs}. Q_k considers the process noise associated with the calculation of equation 10 and 11. Q_{inputs} considers the process noise associated with the input measurement $\boldsymbol{u}_k$.

The measurement noise covariance matrix **R** is determined by the noise of the accelerometer and speed sensors respectively.

The Kalman filter is adaptive in that both noise covariance matrices are altered depending on whether or not the ABS is active or not. The reason for this is that while ABS is inactive, the wheel speeds accurately reflect the vehicle velocity. Conversely, when ABS is active, the wheel speeds are far less representative of the vehicle velocity, and the accelerometer measurement is more reliable. In order to capitalise on this knowledge, both noise covariance matrices are altered to prioritise the accelerometer measurement during ABS braking.

2.4 ABS Algorithm

The ABS algorithm implemented for this paper is the eight phase Bosch algorithm which is defined by slip thresholds and wheel acceleration thresholds. Rangelov (2004) and Reif (2014) describe the fundamental principles of this algorithm and provide insight into the choice of the ABS algorithm parameters. Using this information, the ABS algorithm parameters for the Land Rover test vehicle were chosen as indicated in Table 1.

Table 1. Bosch ABS Algorithm Parameters

Parameter	Symbol	Value
Max Slip	s_{max}	0.1
Acceleration Max	A	30
A max	a_{max}	5
A min	a_{min}	-50

3. Experimental Setup

In order to implement a working ABS algorithm, a variety of hardware and software is required. The tests were conducted on a Land Rover Defender 110 Puma. The following list details the required equipment to ensure accurate ABS testing:

1. Wheel speed sensors for each wheel and required signal analysis hardware/software components.
2. Pressure sensors at each brake calliper to analyse the ABS algorithm's response.
3. Testing facility to conduct experiments
4. Real-time computing system with an interface to other hardware to run the ABS algorithm and different velocity estimators.
5. Modulator control circuit. The function of this is to translate digital signals received from the MicroAutoBox II into power signals which control the ABS modulator coils and pump.
6. Accurate GPS system to measure vehicle velocity and position and accelerometer.

The test vehicle uses variable reluctance sensors for speed measurement. This kind of transducer outputs a sinusoidal wave with a frequency and amplitude proportional to the wheel's rotational speed. A sensor reading circuit was fabricated to convert the sinusoidal wave to an analogue voltage. This is done by reading the sensor signal into an LM1815 chip which outputs a square pulse wave at the same frequency as that of the sinusoidal input. A dsPIC33 was then used to convert the pulse to an analogue output. The dsPIC33 was programmed to reject erroneous pulse inputs that resulted in incorrect speed measurements.

Pressure sensors were installed at each brake calliper to analyse the effect of the ABS algorithm and the ABS modulator on the pressure seen by each wheel.

The tests were conducted on Belgian paving at a vehicle testing facility to simulate rough terrain.

In order to run the ABS algorithm as well as the velocity estimators in conjunction with the vehicle hardware, a real-time operating platform is required. The dSPACE MicroAutoBox II was chosen to run the software aspect of the experiment and to interface it with the wheel speed sensors, pressure sensors, modulator control box and VBox inputs.

In order to control the ABS modulator, circuitry is required to translate the MicroAutoBox's logic level voltage outputs to power level outputs that can control the pump and valve coils of the ABS modulator. A control box was fabricated that was used to interface the MicroAutoBox with the modulator and allow for interfacing between the two systems.

To obtain the Land Rover's true velocity, a Racelogic VBox 3i was installed and set up to communicate the vehicle's exact velocity and position via its CAN bus. The VBox 3i uses DGPS allowing for a tested velocity accuracy of 0.1 km/h (Racelogic, 2016).

Figure 1 shows a schematic of the test vehicle with the required hardware. Figure 2 shows the MicroAutoBox and VBox in the test vehicle as described above. Figure 3 shows the test vehicle at the test facility.

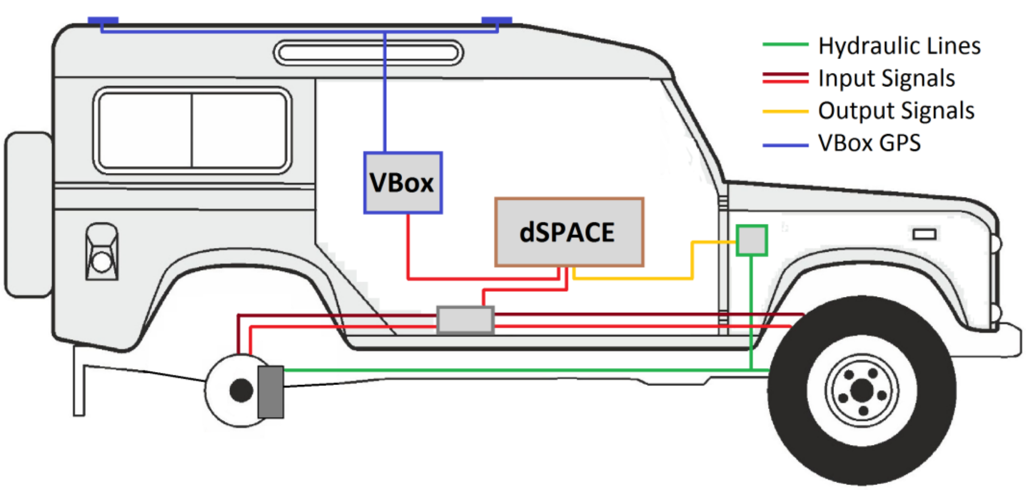

Fig. 1. *Land Rover Test Setup Schematic.*

Fig. 2. *dSPACE MicroAutoBox II and VBox setup in Land Rover*

Fig. 3. *Land Rover with DGPS Base Station on Testing Facility*

4. Results and Discussion

4.1 Performance of Velocity Estimators

Braking tests were performed with ABS on Belgian paving from which vehicle velocity was determined using the Kalman filter, NL estimator and the maximum wheel speed estimator. The results of this experiment are shown in Figure 4 and 5. Figure 4 compares the estimator during braking, as well as the actual velocity of the vehicle (measured by the VBox DGPS system). Figure 5 shows the error of each estimator.

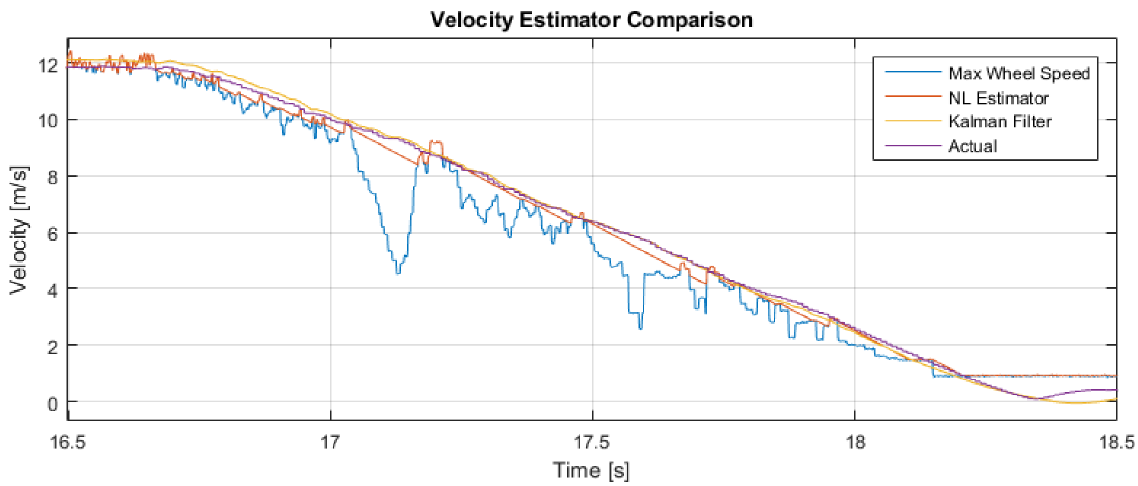

Fig. 4. *Velocity Estimations During ABS Braking*

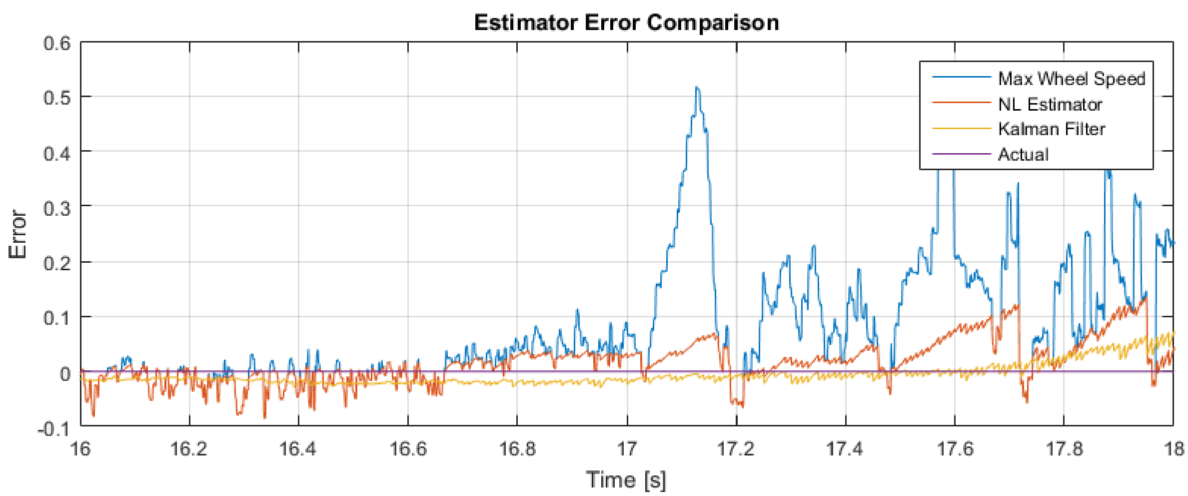

Fig. 5. *Estimation Error Comparison.*

The root mean squared deviation (RMSD) was determined for each estimator and indicated in Table 2. It can be seen that the Kalman filter has an error more than two times smaller than the NL estimator which has an error more than four times smaller than the maximum wheel speed estimator. From these results it is clear that the Kalman filter is far more accurate than the NL estimator which, in turn, is significantly more accurate than the maximum wheel speed estimator.

Table 2. Kalman and Non Linear Estimator Performance Metrics

Velocity Estimator	Root Mean Squared Deviation
Kalman Filter	0.1328
Non Linear Estimator	0.2877
Wheel Speed Max	1.2303

4.2 Theoretical Analysis of Effect of Velocity Estimators on ABS Performance

The Bosch ABS algorithm uses wheel slip as one of its inputs. This implies that the correct calculation of wheel slip is vital to the effective working of the ABS algorithm. If the slip calculation is overestimated, the s_{max} will be reached faster and the brake pressure at that wheel will be reduced. The inverse to this case is also applicable. For both these cases, the brake pressure at each wheel will be suboptimal, implying that increased wheel lock will occur, or braking distance will be increased, both of which are undesirable.

This test was conducted with the ABS algorithm's slip threshold $s_{max} = 0.1$. This analysis revolves around the fact that if the calculated wheel slip is different to the actual wheel slip (assuming constant wheel rolling radius), the threshold will be crossed at a different time, if at all, resulting in suboptimal braking performance

Table 3 shows the results of the slip calculations for each estimator of which a close up is shown in Figure 6. Since the ABS algorithm slip threshold was set to 0.1, every time the actual slip crosses this threshold, a transition is counted. If the slip calculated using the estimators fails to cross the threshold (when the actual slip does), an incorrect transition is noted. The average error for each estimator is determined as $\sum_{FL}^{RR} \frac{incorrect}{transitions} / (4\ wheels)$.

Table 3. Ratio of Erroneous Transitions for Different Estimators

Velocity Estimator	Incorrect				Transitions				Total Error
	FL	FR	RL	RR	FL	FR	RL	RR	
Wheel Speed Max	35	36	37	33					37.1%
Non Linear Estimator	25	23	23	19	96	91	88	93	21.5%
Kalman Filter	13	12	16	10					9.0%

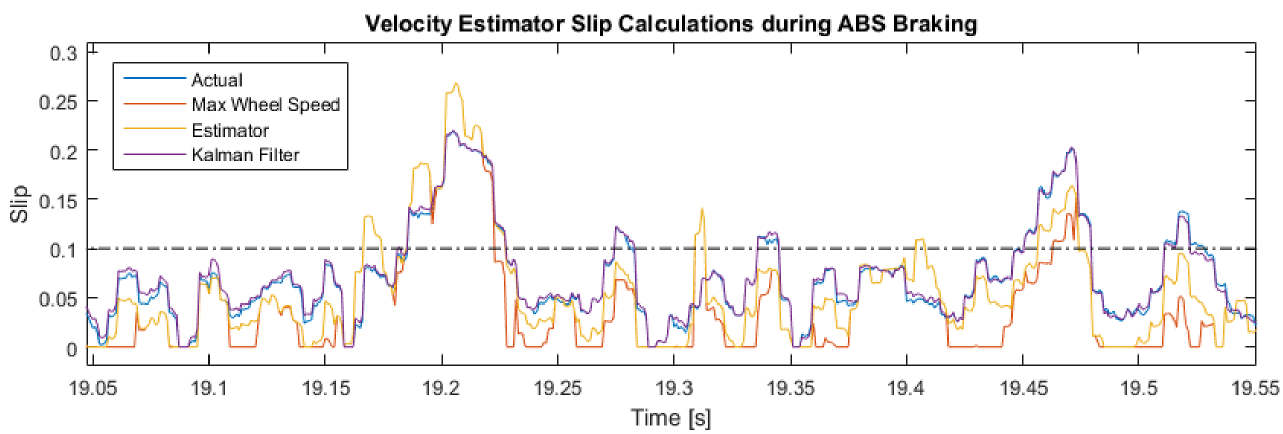

Fig. 6. *Difference in Slip Calculations of Different Velocity Estimators*

From Table 3 it can be seen that the Kalman filter resulted in less than half the errors of the NL estimator which itself resulted in slightly more than half of the errors of the maximum wheel speed estimator. From this result, it can be stated that the Kalman filter will more accurately determine the crossing of the slip threshold, which, in theory, will result in better ABS performance.

This result is, however, theoretical and would need to be validated experimentally. However, due to complications with the ABS modulator control circuit, this could not be done by the time of writing.

5. Conclusion and Recommendations

5.1 Conclusion

From the results presented in Section 4.1, it is evident that the Kalman Filter does indeed estimate the velocity of the vehicle more accurately than the NL estimator and the maximum wheel speed estimator. Since the Kalman filter is not a computationally expensive algorithm, and only requires an additional accelerometer, it should be simple enough to implement in a vehicle to improve the vehicle velocity estimation.

Throughout Section 4.2 it was theorised that the Kalman filter would provide a more accurate slip calculation for an ABS algorithm, which, in turn signifies that the ABS algorithm should more often adjust the wheel speed correctly than with the alternative velocity estimation techniques. Following a theoretical analysis, this proved to be the case. This is, however, only a theoretical statement which still needs to substantiated by experimental results.

5.2 Comments on the Adaptive Kalman Filter

The proposed adaptive Kalman filter proved to yield more accurate results than the NL estimator and maximum wheel speed estimator. It is clear that the adaptive strategy of prioritising the accelerometer measurements during ABS braking ensures an accurate estimate of the vehicle velocity compared to the other estimators. Even though the performance of ABS using this Kalman filtered vehicle velocity could not be proven experimentally, it was theorised that it would indeed yield more accurate slip calculations.

Future work on this adaptive Kalman filter could involve a more discretized adaption of the measurement noise covariance matrix depending on the number of wheels in lock up. This could potentially lower the effect of integration drift when the Kalman filter prioritises the accelerometer during ABS braking.

5.3 Recommendations for Future Work

The next steps of this project would entail the implementation of the different vehicle velocity estimators into the Bosch ABS algorithm and measuring the braking performance of the vehicle. Validation of theoretically increased performance using the adaptive Kalman filter as opposed to a normal Kalman filter or the NL estimator would also be validated with such an experiment.

Nomenclature

a	acceleration
a_b	Measurement bias
$\mathbf{B}$	Control input model matrix
$\mathbf{H}$	Observation matrix
$\mathbf{K}$	Optimal Kalman gain
$\mathbf{P}$	a posteriori error covariance matrix
$\mathbf{Q}$	Process noise covariance matrix
$\mathbf{R}$	Measurement noise covariance matrix
$\mathbf{S}$	Residual covariance matrix
Δt	step time
v	velocity
$\mathbf{x}$	a posteriori state estimate vector

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