2013 European Control Conference (ECC)
July 17-19, 2013, Zürich, Switzerland.

Wheelie detection for single-track vehicles

Giulio Panzani*, Matteo Corno** and Sergio M. Savaresi**

***Abstract*— Single-track vehicles electronic control systems have been experiencing an important growth in the last years. Despite some similarities with four-wheeled vehicles the dynamics of two-wheeled vehicles have some unique features that require ad hoc solutions. One of those is the lift of the front wheel from the ground during severe accelerations, usually known as *wheelie*. This phenomenon is particularly important since, if not controlled, can lead to vehicle instabilities. Moreover, it has a significant impact on the vehicle longitudinal speed estimation, essential for the development of wheel slip-based traction control systems, so widely spreading. In this paper the problem of detecting a wheelie occurrence is discussed. Two algorithms, that employ only standard vehicle equipment sensors, are presented. Their parameter tuning procedure is described and experimental data are used to show their effectiveness, as well as for a performances comparison.**

I. INTRODUCTION

The front wheel lift - usually referred as *wheelie* - is a common phenomenon that can occur in single-track vehicles: as depicted in Figure 1, during a wheelie the front wheel is completely detached from the ground and the vehicle proceeds only thanks to the rear wheel.

Fig. 1. A sport motorbike performing a wheelie.

The wheelie phenomenon is related to the vertical load transfer that occurs during the vehicle longitudinal motion, that is particularly emphasized in single-track vehicles. According to a simplified vertical forces balance, see for example [14], the vertical load F_{zf} that the front wheel exchanges with the road surface has the following expression:

$$F_{zf} = \quad F_{zf0} - m\frac{h}{l}\ddot{x}.$$

Thus, proportionally to the vehicle acceleration $\ddot{x}$, the front vertical force diminishes with respect to the zero acceleration value F_{zf0} (function of mass and vehicle geometry). It is interesting to notice how the decrease is proportional through the gain factor $m\frac{h}{l}$, where m is the mass of the vehicle (chassis and driver) and $\frac{h}{l}$ is the ratio between the height of the center of mass h and the vehicle wheel base l. In motorcycles this ratio is higher (approximatively double) with respect to the four-wheeled vehicle one, and that is why this phenomenon is particularly relevant in these vehicles.

In the development and design of two-wheeled vehicles control systems, information on wheelie occurrence have to be included. Despite the catching and spectacular nature of such maneuver, due to its potentially unstable behaviour (that can cause vehicle overturning) ad hoc engine torque control systems have been recently proposed (see *e.g.* [13], [6]): a wheelie detection algorithm to trigger the activation/deactivation of such controllers is however required. Generally speaking, also other vehicle dynamic control systems exploit information about the occurrence of this event. For example, the so well-reputed slip based Traction Control systems (e.g. [9]) that require an estimate of the vehicle body speed during traction maneuver. As discussed in [11] the vehicle speed estimate, based on front wheel speed and longitudinal acceleration data-fusion, is no more reliable when a wheelie occurs: hence in case of wheelie, its detection becomes a consistency flag for vehicle speed estimate. It is not difficult to extend these considerations for other electronic systems, such as semi-active suspension (see *e.g.* [15]) or advanced stability control systems (see *e.g.* [5]).

To the best of the authors knowledge, this topic has never been treated in the open scientific literature. Some patents can be found (see [6], [7]) where basically wheelie is detected by comparing vehicle acceleration with a specific threshold opportunely tuned. From equation (1) it can be easily noticed how such an approach is quite sensitive, for example, to the vehicle and rider mass that can experience important variations.

Thus, pushed by the aforementioned technological reasons, in this paper two wheelie detection algorithms are presented, validated and compared using real experimental data. From the analysis of the measured signals during a wheelie, the key idea of comparing front wheel speed and longitudinal acceleration signals is introduced. The first algorithm detects wheelie by simply applying such experimental evidence,

*G.Panzani is with the Department of Mechanical and Structural Engineering, Universitá degli studi di Trento, Via Mesiano 77, I-38123 Trento, Italy. E-mail: giulio.panzani@ing.unitn.it.

**M. Corno and S.M. Savaresi are with the Dipartimento di Elettronica e Informazione, Politecnico di Milano, Piazza Leonardo da Vinci 32, 20133 Milano, Italy. E-mail:corno,savaresi@elet.polimi.it.

The work has been partially supported by MIUR project "New methods for Identification and Adaptive Control for Industrial Systems".

Corresponding author: G. Panzani, Dipartimento di Ingegneria Meccanica e Strutturale, Universitá degli studi di Trento, Via Mesiano 77, I-38123 Trento, Italy, e-mail: giulio.panzani@ing.unitn.it

978-3-952-41734-8/©2013 EUCA

whereas for the second one the problem is solved with a *fault detection* approach. Particular attention is devoted to obtaining reliable, easily implementable and cost-effective techniques that make use of electronics and sensors already available on standard production vehicles. A comparison between both algorithms, based on experimental data, is traced considering their wheelie detection performances and their robustness with respect to different vehicle operating modes.

The paper is organized as follows: in Section II the experimental setup is presented. In Section III the principles of wheelie detection and the mentioned algorithms are discussed. In Section IV guidelines for algorithms tuning are shown and a performances comparison among the proposed algorithms is presented.

II. EXPERIMENTAL SETUP

The wheelie detection is meant for high-end sport motorcycles, due to the high acceleration they can reach: this is the kind of vehicle referred in this work to validate the detection strategies. It is equipped with the following sensors:

- Front and rear wheel encoders. The motorcycle is equipped with two hall-effect encoders with 48 teeth. The discrete position encoder information is used to estimate the angular wheel velocity using the $1/\Delta T$ method ([3]). This algorithm provides an accurate estimation of the wheel velocity at low frequency, but it is affected by considerable disturbances at high frequency. It is not also uncommon to measure a periodic high frequency noise related to the wheel rolling frequency and its harmonics (see [12]).
- A 1-axis MEMS longitudinal accelerometer. Typically, acceleration measures are affected by low frequency noise and drift. The most important noise source is the effect of gravity on the acceleration measurement, due to a non perfect horizontal alignment of the measurement axis.
- Suspension stroke sensors. They provide a measurement of the suspension elongation. They can be used to estimate the load on the wheels and be used to detect a wheelie. Stroke sensors are currently not installed on production vehicles and are here employed as *reference* to validate the proposed methods.

III. WHEELIE DETECTION ALGORITHMS

According to the description of the phenomenon provided in the introduction, it is clear that the detection of a wheelie could be easily done at least in two ways:

1) Measuring the front suspension elongation. During acceleration the front suspension extends until it reaches its maximum length: at this instant the wheelie occurs. Despite being the most direct way to detect a wheelie, the linear potentiometers (or LVDT) used to measure suspension elongation are expensive and fragile sensors, not suited for industrialization.
2) Measuring the vehicle pitch angle. The geometry of the suspension is such that its maximum elongation corresponds to a known pitch angle (with respect to the road). A threshold on the pitch angle would therefore be an effective detection method. Unfortunately, a direct measure of the pitch angle is not available and estimation techniques through inertial measurements (see e.g. [1]) are at their infancy.

To overcome the limitations of the mentioned solutions, in this paper two wheelie detection algorithms are presented and compared. They employ only the measurements available on a standard production motorcycle. Moreover, unlike vehicle attitude estimation algorithms - usually based on (Extended/Unscented) Kalman filters estimators, see *e.g* [1], [2] - the proposed solutions require a low computational effort, thus making them suitable for industrialization. Being based on *indirect* information on wheelie occurrence (as will be clear in the following), a delay with respect to *direct* method (*i.e.* front suspension elongation) is expected. However, the proposed algorithms are able to detect a wheelie in approximately less than 0.1 seconds: as discussed in [11], this is the maximum time span allowed to prevent undesired interventions of high-level vehicle dynamic control systems.

The common idea behind both algorithms can be intuitively introduced by inspecting Figure 2. During a wheelie,

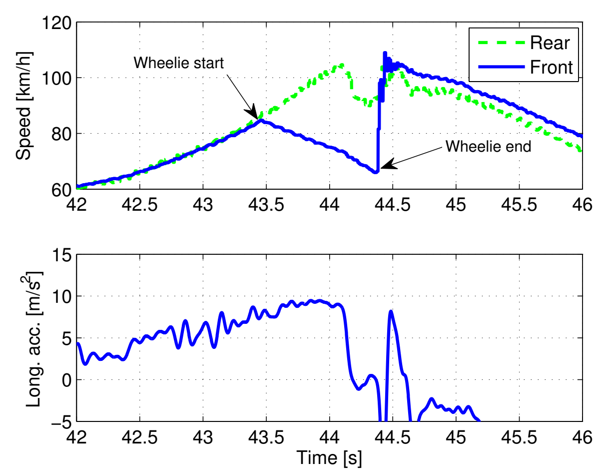

Fig. 2. Wheels speed and measured longitudinal acceleration during a wheelie.

a discrepancy between the front wheel speed (v_f) and the vehicle longitudinal acceleration (a_x) can be noticed: the front wheel angular speed decreases whereas the vehicle continues to accelerate. The front speed slowing is caused by the rolling resistance forces (*e.g.* due to the roll bearings) that, as the front tire detaches from the ground, are the only one acting on the wheel. Conversely, during the normal vehicle motion, the longitudinal force due to the contact between the tire and the road guarantees the front wheel acceleration.

This discrepancy is at the basis of the two wheelie detection algorithms, introduced in the following subsections.

`Basic` *algorithm*

The first algorithm introduced is based on the direct comparison between the vehicle longitudinal acceleration signal and front wheel acceleration (a_f) derived by the measure v_f.

During a normal acceleration, as discussed in [11], the torques applied to the front wheel are negligible and only a little longitudinal force is required to balance them. Thus, the front wheel slip λ_f (see [10] for its definition) can be neglected, meaning that the front wheel speed $\omega_f R_f$ (wheel angular speed times wheel rolling radius) is equal to the vehicle one v.

$$\lambda_f = \frac{\omega_f R_f - v}{v} \approx 0 \Rightarrow v_f = \omega_f R_f = v \qquad (1)$$

The same conclusion can be hence transferred on the acceleration measurements:

$$a_f = \dot{\omega}_f R_f = a_x$$

This equality is at the basis of the first algorithm: during the normal vehicle motion, longitudinal vehicle and front wheel acceleration should be similar; since during wheelie these measurements are significantly different, a discrepancy (Δ) between them is used to trigger the wheelie event detection.

Despite the simplicity of the proposed approach, some wariness is needed. In fact beside wheelie, there are some other factors that cause differences between vehicle and front wheel acceleration. Among the most significant the vertical vehicle dynamic that, due to the non zero vehicle caster angle (see [4]) can influence the longitudinal acceleration signal (remember that usually the IMU is located on the vehicle main frame). Signals noise cannot be disregarded: in particular, the periodic, frequency varying noise typically present on wheel speed measurement - whose origin is discussed in [12] - significantly worsen the front speed acceleration signal (computed with a linear high-pass filter). Finally, there are several situations in which the hypotheses in (1) are not valid: during a braking maneuver for example, in which the front wheel slip is no longer negligible, the equality between vehicle and front wheel acceleration is no longer valid.

For all these reasons, the `Basic` algorithm is modified accommodating the following features:

- a low pass filter for the longitudinal acceleration used to suppress high frequency noise (whose output is called $\hat{a}_x$);
- a first order high-pass filter used to compute the front wheel acceleration $\hat{a}_f$;
- a finite state machine, depicted in Figure 3, that enables the comparison between the mentioned signals only when opportune.

When the `Idle` state is active, the wheelie detection algorithm is deactivated; while in `Running`, the wheelie detection algorithm is executed:

$$\hat{x}_{\text{wh}} = \begin{cases} 0 \text{ (normal mode) if } \hat{a}_x - \hat{a}_f < \Delta \\ 1 \text{ (wheelie mode) if } \hat{a}_x - \hat{a}_f > \Delta \end{cases} \qquad (2)$$

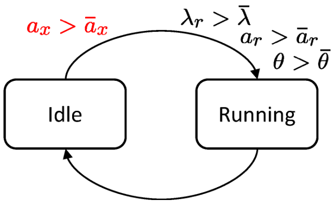

Fig. 3. Finite state machine pictorial representation.

As previously discussed, the algorithm (2) provides correct information only when a wheelie is actually possible. Thus the transition between `Idle` and `Running` state is triggered by a series of conditions that indicate that the vehicle motion is such that a wheelie could occur. Intuitively, the most important check is when th vehicle longitudinal acceleration a_x overcomes a certain threshold (indicated with the bar symbol). However, to improve the finite state machine robustness and avoid state chattering, also other conditions, related to vehicle acceleration/wheelie, can be added (*i.e* on rear slip/rear traction force λ_r, on rear wheel acceleration a_r, on throttle angle θ). The inverse transition is opposite with respect to the described one.

`Fault detection` *based algorithm*

The second algorithm proposed in this paper is based on the same mismatch observed between vehicle and front wheel acceleration, but tackles the problem with a genuine *Fault Detection* approach (see [8]). To solve the wheelie detection problem, two dynamic models for the two operating modes (`normal` and `wheelie`) are derived and two distinct state estimators are designed, one for each operating mode. Since the dynamics are different, it is expected that each estimator provide a small estimation error (residual) when the corresponding operating mode is ongoing, whereas the estimate provided by the non-active mode state observer will significantly differ from the measured signal. As a consequence, the wheelie event is detected by simply monitoring which one is the lower residual state observer.

The dynamic models that characterize each operating mode are here derived. For the `normal` mode, the assumption of zero front wheel speed previously introduced leads to the following dynamic model:

$$\begin{aligned} \dot{v}_f \sim \dot{v} &= a_x + \eta_1 \\ v_f &= v + \epsilon_1. \end{aligned} \qquad (3)$$

The first equation states that, due to the negligible slip, the front wheel acceleration can be approximated with the vehicle acceleration $\dot{v}$, measured by the accelerometer a_x. An additive white noise η_1 is added to include noise and model uncertainties. The second equation describes the wheel speed signal, equal to the vehicle speed plus a term ϵ_1 that accounts for measurement noise.

The dynamic model for the `wheelie` operating mode is reported in equation (4):

$$\begin{aligned} \dot{v}_f &= -\delta + \eta_2 \\ v_f &= v + \epsilon_2. \end{aligned} \qquad (4)$$

In this model the uncorrelation between vehicle acceleration and front wheel speed is evident, since a_x is not even included in the equations. The evolution of the angular speed is described in the first equation with a constant deceleration $\delta > 0$ as the experimental evidence (see Figure 2) suggests; again an additive noise η_2 has been included. The second equation describes the noisy (ϵ_2) front wheel speed signal. All noises are assumed to be uncorrelated gaussian white noise with variance $q_{1|2}$ for the model disturbances, and $r_{1|2}$ for the measurement noises.

Each state observer for models (3) and (4) is designed as steady state Kalman filter estimators:

$$\dot{\hat{v}} = A\hat{v} + B\,u + K\,(y - C\,\hat{v}) \tag{5}$$

where K is the Kalman gain, $\hat{v}$ the estimated front wheel speed, u and y the respective input and output, according to the discussed dynamic models. Each filter provides its own front wheel velocity estimate: $\hat{v}_{nw}(t)$, corresponding to the `normal` condition, and $\hat{v}_w$(t), corresponding to the `wheelie` condition. Dealing with first order dynamic systems, it is simple to derive the analytic expression for the mentioned estimators. In particular it can be shown that:

$$\begin{aligned} \dot{\hat{v}}_{nw} &= -\frac{\alpha_1}{r_1}\hat{v}_{nw} + a_x + \frac{\alpha_1}{r_1}v_f \\ \dot{\hat{v}}_w &= -\frac{\alpha_2}{r_2}\hat{v}_w - \delta + \frac{\alpha_2}{r_2}v_f \end{aligned} \tag{6}$$

where $\alpha_1 = \sqrt{q_1 r_1}$, $\alpha_2 = \sqrt{q_2 r_2}$. Notice that, for each model, the Kalman filter is compound by two first order filters (one for the acceleration/deceleration contribution and the other for the front wheel speed signal), thus making the implementation of such estimators easy.

The wheelie detection algorithm is based on the analysis of the residual, defined as:

$$\begin{aligned} e_{nw}(t) &= (v_f(t) - \hat{v}_{nw}(t))^2 \\ e_w(t) &= (v_f(t) - \hat{v}_w(t))^2\,. \end{aligned} \tag{7}$$

The estimator with the lowest residual, indicates the current operating mode. Thus the wheelie detection algorithm can be easily implemented:

$$\hat{x}_{\text{wh}} = \begin{cases} 0\ (\texttt{normal}\ \text{mode})\ \text{if}\ e_{nw} < e_w \\ 1\ (\texttt{wheelie}\ \text{mode})\ \text{if}\ e_{nw} > e_w \\ N.D.\ (e_{nw}, e_w) > \bar{e} \end{cases} \tag{8}$$

Being based on two dynamic models - that describe signals relationships during the two operating modes - any other working condition (*e.g.* braking) results in a very high residual for both models. Thus, an additional value has been added to the possible $\hat{x}_{\text{wh}}$: the N.D., that indicates the Not Defined wheelie status, since residuals are too high.

It is worth noting that during a braking maneuver, if the vehicle decelerates of δ [m/s^2] the `wheelie` dynamic model in equation (4) perfectly describes signals relationships even when wheelie is not ongoing. Thus, even for the second algorithm a finite state machine that triggers the wheelie algorithm evaluation is suggested: the same finite state machine used for the first algorithm presented, can be employed.

Remark A mismatch similar to the one among vehicle acceleration and front wheel speed can be appreciated also among the rear and the front wheel speed (see Figure 2). In principle, one can think to avoid using the longitudinal vehicle acceleration, thus saving the employment of such sensor. However it should be stressed that, due to the non negligible rear wheel slip during the acceleration maneuver, the rear wheel acceleration is not equal to the front wheel one (even when wheelie does not occur).

$$\dot{\omega}_r R_r = \dot{\lambda}_r v + \lambda_r \dot{v}$$

As a consequence, a difference between these signals cannot be directly used to detect the wheelie event: some additional informations on the amount of rear wheel slip, or finite state machine additional complexity (required to discriminate signal mismatch not due to wheelie) would be required.

IV. EXPERIMENTAL VALIDATION

In this section both algorithms proposed are applied and compared on real experimental data. Moreover, guidelines for parameter tuning are provided. The following figures show the main algorithms' signals presented in the previous Section, applied to the wheelie example shown in Figure 2. In Figure 4 the filtered longitudinal acceleration $\hat{a}_x$ and the front wheel one $\hat{a}_f$ are shown. The ongoing wheelie is detected when the difference $\Theta = \hat{a}_x - \hat{a}_f$ overcomes the threshold value Δ.

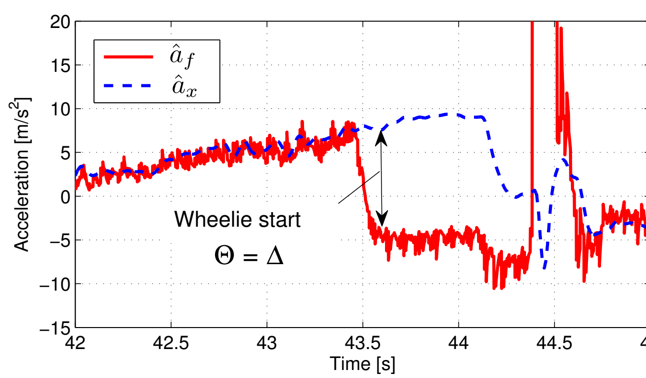

Fig. 4. `Basic` wheelie detection algorithm example.

The upper panel in Figure 5 shows the estimated speed signals, $\hat{v}_{nw}$ and $\hat{v}_w$ along with the front wheel speed. It can be appreciated how each speed estimate fits the front wheel speed during the corresponding operative mode. Comparing the residuals, shown in the lower panel, the ongoing wheelie is detected.

The presented algorithms depend on some parameters that should be properly tuned in order to achieve the best detection performances. As discussed in Section III, in particular:

- the `Basic` algorithm parameters are the two cut-off frequencies for the 1^{st} order filters used to estimate the two accelerations, and the threshold Δ;
- the `Fault Detection Based` algorithm parameters are the two cut-off frequencies for the 1^{st} order filters used to estimate the two velocities.

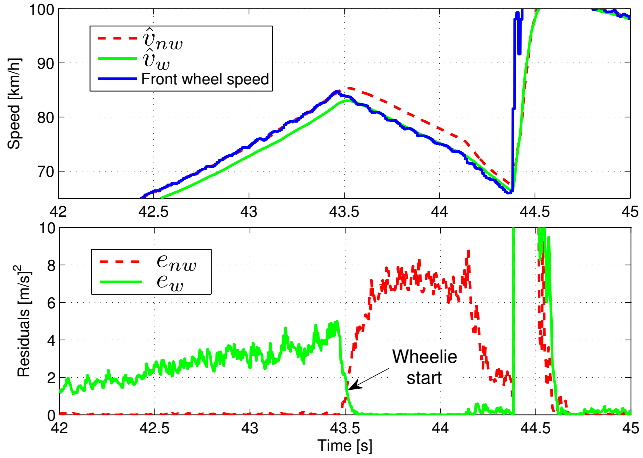

Fig. 5. `Fault Detection Based` wheelie detection algorithm example.

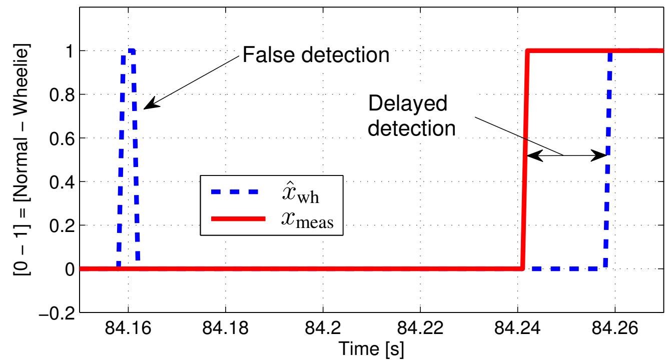

Fig. 6. False and delayed detection examples.

The tuning of such parameters aims at maximizing the estimation performances of each algorithm. To do so, the following cost function is introduced:

$$J = \frac{\int |x_{\text{meas}} - \hat{x}_{\text{wh}}| dt}{\int x_{\text{meas}} dt} \tag{9}$$

where x_{meas} and $\hat{x}_{\text{wh}}$ are, respectively, the real/measured operating mode (coming from the front suspension stroke sensor as explained in Section III) and the estimated one. Thus, J cumulates the differences between the real and the estimated vehicle status: the smaller the cost function, the better are the algorithms detection performances. According to this principle, all algorithms' parameters are found minimizing the cost function:

$$\bar{\vartheta} = \min J_{\vartheta}$$

where, ϑ is the set of parameters to be tuned for each algorithm and $\bar{\vartheta}$ are the values that minimize the cost function J.

Figure 6 helps to point out how algorithm detection errors can be twofold:

1) *false detection*: the algorithm detects a wheelie ($\hat{x}_{\text{wh}} = 1$) when it is not ongoing ($x_{\text{meas}} = 0$);

$$\begin{cases} J_{false} = \dfrac{\int |e| dt}{\int x_{\text{meas}} dt} \\ e = x_{\text{meas}} - \hat{x}_{\text{wh}}, \text{ when } e < 0 \end{cases} \tag{10}$$

2) *delayed detection*: the algorithm does not detect the wheelie event when it occurs ($\hat{x}_{\text{wh}} = 0$, $x_{\text{meas}} = 1$). As suggested by the Figure, a certain amount of time is needed by the algorithm to detect a wheelie. This is the drawback to be accepted when using *indirect* detection methods.

$$\begin{cases} J_{delay} = \dfrac{\int |e| dt}{\int x_{\text{meas}} dt} \\ e = x_{\text{meas}} - \hat{x}_{\text{wh}}, \text{ when } e > 0 \end{cases} \tag{11}$$

Notice that $J = J_{false} + J_{delay}$.

Not surprisingly, there is a natural trade-off between this two quantities: a very fast algorithm (*i.e* with a very small detection delay) provides an higher number of false detections; conversely, making the algorithm robust with respect to false detection leads to an higher average detection delay. Since the cost function (9) includes indistinctly both elements, the parameters tuning procedure - that minimize the mentioned cost function - provides the parameters values that solve this natural trade-off.

Considering the `Fault Detection` based algorithm, the algorithm tuning procedure is done optimizing the cost function J with respect to the two mentioned parameters. As an example, in Figure 7 the cost function J for different values of estimators cut-off frequencies (here called ω_{nw} and ω_{w}) is shown. In the Figure, beside the cost function J, the *false* and the *delayed* detections are also reported, in order to better appreciate the discussed performance trade-off. A

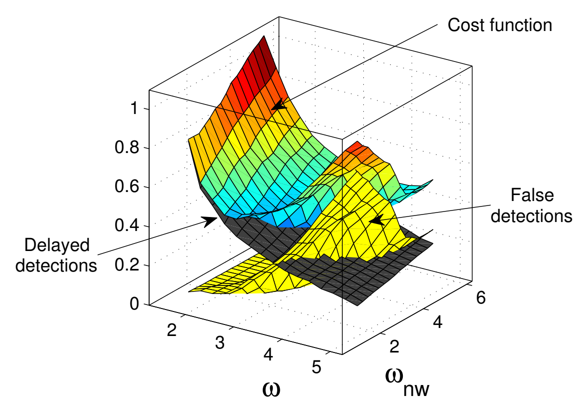

Fig. 7. Tuning cost function for different algorithm parameters values. `Fault detection` based algorithm.

similar optimization procedure is carried for the `Basic` wheelie detection algorithm. However, it takes additional time/effort since this algorithm depends on three parameters.

To compare the detection performances of the proposed algorithms, two different data set have been considered. The first one, called `A`, is an *ad hoc* test in which subsequent wheelies are performed. This kind of test has been selected

Dataset A	J_{A}	τ_A	$J_{f\%\,A}$	J_{B}	τ_B	$J_{f\%\,B}$
BS	0.0395	0.023	0.7	0.0713	0.044	1.1
FD	0.0606	0.038	0.9	0.0649	0.041	0.8

TABLE I

ALGORITHM DETECTION PERFORMANCES ON DATASET A

Data set B	J_{A}	τ_A	$J_{f\%\,A}$	J_{B}	τ_B	$J_{f\%\,B}$
BS	0.3794	0.039	17.6	0.3340	0.045	9.6
FD	0.3790	0.041	16.4	0.3656	0.045	12.7

TABLE II

ALGORITHM DETECTION PERFORMANCES ON DATASET B

as representative of a standard (very easy to perform and not time consuming) test that can be used for end-of-line parameters calibration. The second set B is made by data collected during a real track session, as representative of an usual vehicle usage.

In Table I and II the performances are compared, respectively, for the A and B datasets. In each table, two columns are reported: one that summarizes the detection performances with algorithm parameters tuned on the same dataset; the other shows the algorithm performances when parameters are obtained using the other dataset for the optimization procedure. Three performances indicators are provided:

1) the overall cost function value J, as defined in (9)
2) the average detection delay τ, in seconds, computed as:

$$\begin{cases} \tau = \dfrac{\int |e| dt}{\#\ \text{wheelies}} \\ e = x_{\text{meas}} - \hat{x}_{\text{wh}},\ \text{when}\ e > 0 \end{cases} \quad (12)$$

3) the percentage of false detections, $J_{f\%} = J_{false} \cdot 100$.

The presented results allow the following considerations

- In general, both algorithms provide satisfactory performances: in each of the considered situation, it can be seen how the average detection delay is less than the required 100[ms].
- The BS algorithm achieves the better detection performances: for both datasets the best cost function value is obtained by employing this algorithm (on the same dataset used for tuning). Its additional parameter, despite binding to a longer tuning procedure, explains the higher performances of such algorithm.
- The FD algorithm provides more robust/constant performances: despite the significantly different dataset nature, the parameter optimization procedure for algorithm A leads to the same final parameter values. It is particularly interesting to notice how the average detection delay keeps similar in all the situations; the same thing does not happen for the algorithm BS that shows an higher sensitivity to the dataset used for its parameters tuning (*i.e.* a 90% change in the average detection delay for dataset A and 14% for dataset B).

V. CONCLUSIONS

In this paper the problem of detecting the wheelie of a single track vehicles has been tackled. Two detection strategies have been presented and compared using real experimental data: both employ standard vehicle sensors and result in low computational power algorithms. Both are based on the experimental mismatch that occurs between vehicle acceleration and front wheel speed signals during a wheelie: the first algorithm directly implement this intuitive idea, the second one solves the problem with a fault detection approach. These algorithm proves to be somehow complementary: the first one can achieve higher detection performances, thanks to its higher number of parameters, making that algorithm interesting for highly demanding applications (such as race/competitions). The second one is more suited for an industrial application, due to the small number of parameters to be tuned and due to its more robust performances, with respect to different vehicle operating conditions.

REFERENCES

[1] I. Boniolo, S. Corbetta, and S. Savaresi, "Attitude estimation of a motorcycle in a kalman filtering framework," in *Proc. 6th IFAC Symposium Advances in Automotive Control, AAC 2010, Munich, Germany*, 2010, pp. 779–784.

[2] S. Corbetta, I. Boniolo, and S. Savaresi, "Attitude estimation of a motorcycle via unscented kalman filter," in *Proc. IFAC Symposium on Mechatronic Systems, Cambridge, Massachusetts, USA*, 2010, pp. 511–516.

[3] M. Corno and S. Savaresi, "Experimental identification of engine-to-slip dynamics for traction control applications in a sport motorbike," *European Journal of Control*, vol. 16, no. 1, pp. 88–108, 2010.

[4] V. Cossalter, *Motorcycle dynamics*. Lulu.com, 2006.

[5] P. De Filippi, M. Tanelli, M. Corno, and S. Savaresi, "Enhancing active safety of two-wheeled vehicles via electronic stability control," in *Proc. 18th IFAC World Congress, Milano, Italy*, 2011, pp. 638–643.

[6] T. Hasegawa, "Wheelie prevention device for a motorcycle and method for preventing a wheelie of a motorcycle," Nov. 5 2003, eP Patent 1,184,272.

[7] ——, "Acceleration sensor and engine control for motorcycle," Oct. 24 2006, uS Patent 7,124,852.

[8] R. Isermann, *Fault-diagnosis systems: an introduction from fault detection to fault tolerance*. Springer Verlag, 2006.

[9] T. Johansen, I. Petersen, J. Kalkkuhl, and J. Ludemann, "Gain-scheduled wheel slip control in automotive brake systems," *Control Systems Technology, IEEE Transactions on*, vol. 11, no. 6, pp. 799–811, nov. 2003.

[10] H. Pacejka, *Tyre and vehicle dynamics*. Butterworth-Heinemann, 2005.

[11] G. Panzani, M. Corno, and S. Savaresi, "Longitudinal velocity estimation in single-track vehicles," in *Proc. 16th IFAC Symposium on System Identification, SYSID 2012, Brussels, Belgium*, 2012, pp. 1257–1262.

[12] ——, "On the periodic noise affecting wheel speed measurement," in *Proc. 16th IFAC Symposium on System Identification, SYSID 2012, Brussels, Belgium*, 2012, pp. 1257–1262.

[13] G. Panzani, M. Corno, S. Savaresi, L. Fabbri, A. Ricci, F. Fioravanzo, and P. Lisanti, "Metodo per il riconoscimento dell'impennata e per la gestione della trazione in un motoveicolo," Italian Patent MI2010A000878, 2010.

[14] G. Panzani, S. Formentin, and S. Savaresi, "Active motorcycle braking via direct data-driven load transfer scheduling," in *Proc. 16th IFAC Symposium on System Identification, SYSID 2012, Brussels, Belgium*, 2012, pp. 1257–1262.

[15] S. Savaresi, C. Poussot-Vassal, C. Spelta, L. Dugard, and O. Sename, *Semi-active suspension control design for vehicles*. Butterworth-Heinemann, 2010.