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Online Estimation of Vehicle Inertial Parameters for Improving Chassis Control Systems

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Abstract:
Vehicle chassis control systems aim at increasing vehicle safety and performance, while ensuring superior passenger comfort. Nearly all control algorithms are sensitive to the inertial parameters of a vehicle. As the vehicle mass, the moments of inertia, and the centre of gravity (COG) position can change significantly during operation, an accurate online estimation of these properties could substantially improve the performance of an active system. This paper presents an innovative algorithm for the online estimation of the inertial parameters of a road-vehicle. Using low-frequent suspension displacement signals and suspension stiffness characteristics, the vehicle mass and horizontal COG position are estimated. A Monte Carlo method determines the most probable mass distribution. Based on the assigned passenger weight, anthropometric data sets allow to calculate the inertial properties of every passenger, eventually resulting in the inertial parameters of the complete, loaded vehicle. The accuracy of the proposed algorithm is validated by means of a test campaign on an accurate kinematics and compliance testrig.

Keywords: Automotive Control, Vehicle Suspension, Parameter Estimation, Monte Carlo Simulation, Moments of Inertia

1. INTRODUCTION

Intelligent vehicle systems are increasingly contributing to the vehicle value. Consequently, design engineering and optimization methodologies have to support the specific mechatronic nature of such systems [Van der Auweraer et al. (2009)].

In this context, vehicle chassis control systems, such as electronic yaw stability control [Kiencke and Nielsen (2005)] and (semi-)active suspension systems [Savaresi et al. (2010)], have been a very active field of research during the last few decades, mainly due to their potential to significantly improve vehicle safety and passenger comfort. The design of a chassis control system is a complex engineering problem, addressing vehicle safety, road handling, body motion, and ride comfort, leading to an extensive range of control algorithms [Hrovat (1997), Canale et al. (2007)].

Virtually all of these algorithms are sensitive to the vehicle inertial parameters, including the vehicle mass, the moments of inertia, and the position of the centre of gravity (COG). Considering that these inertial parameters can vary significantly during operation, e.g. due to the number of passengers and the loading condition, control performance can substantially be improved by an accurate online estimation of these inertial parameters.

Although the importance of the inertial parameters on vehicle stability and handling has been shown [Allen et al. (2003)], most automotive manufacturers usually assume the inertial parameters to be fixed and rely on robust control strategies to account for the parameter variations, leading to a conservative design for the worst case scenario. The inertial properties are obtained from measurements on a Kinematics & Compliance (K&C) testrig or are simply derived from regression equations relating them to typical vehicle dimensions, as presented by Allen et al. (2003). Obviously these approaches do not take into account the potential load variation during the vehicle's operation.

Different online methods for estimating the inertial properties of a vehicle have been reported in literature, as presented in section 2. Algorithms can mainly be distinguished based on the available sensor signals and the employed vehicle models. The innovative estimation algorithm presented in section 3 was originally developed to be adopted in the control algorithm of an active suspension system and can therefore use information on the suspension displacements. The algorithm distributes the payload mass over the passenger positions using a Monte Carlo method and employs anthropometric data tables to compute the inertial properties of each passenger, eventually resulting in the total vehicle's inertial properties. Section 4 shows the accuracy of the method by comparing the estimation results with accurate data from a K&C measurement campaign.

2. REPORTED METHODS FOR INERTIAL PARAMETER ESTIMATION

The literature presents a multitude of algorithms for the online estimation of vehicle inertial properties. As estimation procedures are commonly focussed on one specific inertial property, the algorithms will be classified based on whether they estimate the *vehicle mass*, the *moments of inertia*, or the *COG position*.

Furthermore, approaches can be subdivided based on their updating procedure: an *event-based algorithm* will perform and update its estimation only during specific events (e.g. gear shifting, sharp cornering, etc.), while an *averaging* algorithm will do this continuously. [Fathy et al. (2008)]

A final basis for classification consists of the dynamics that are used by the algorithm for the estimation: we distinguish between *longitudinal dynamics*, *lateral/yaw dynamics*, *powertrain dynamics*, *suspension dynamics*, or any mutual combination. Commonly, the estimation of an inertial parameter is based on the dynamics that are most sensitive to that particular parameter.

2.1 Vehicle Mass Estimation

The mass of a vehicle is potentially the most crucial parameter for any kind of dynamics of a road vehicle, as it directly affects the longitudinal, lateral, powertrain, and suspension dynamics. On the other hand, this parameter can vary significantly during vehicle operation: passengers, luggage, and fuel can easily increase the mass of an empty passenger vehicle with several hundred kg. Consequently, it is an important system parameter for yaw stability control, adaptive cruise control, powertrain control, suspension control, etc.
The review will further classify the reported mass estimation methods based on the various observed dynamics.

Longitudinal Dynamics Many researchers have capitalized on the relation between the vehicle mass, the longitudinal forces, and the resulting longitudinal acceleration. Bae et al. (2001) proposed an averaging recursive least-squares method for estimating the vehicle mass, using road grade measurements based on GPS data, the longitudinal acceleration, and the driving force. Vahidi et al. (2005) employed a similar recursive least-squares method with multiple forgetting factors in order to estimate the vehicle mass and the road grade simultaneously. To improve the parameter identifiability, Winstead and Kolmanovsky (2005) proposed an active approach for estimating the road grade and the vehicle mass by combining an extended kalman filter (EKF) and a model predictive control (MPC) method for controlling the engine torque.

The event-based algorithms mainly capitalize on the fact that sharp longitudinal accelerations or decelerations are highly sensitive to the vehicle's mass. Based on this idea, the patented approach by Breen (1996) estimates the vehicle mass during controlled vehicle decelerations based on braking pressure measurements. Genise (1996) suggested to consider the velocity drop during gear shift maneuvers.

Lateral/Yaw Dynamics Best et al. (2006) developed an identifying extended Kalman filter that estimates the vehicle mass, the yaw inertia and the longitudinal COG position, based on the vehicle's lateral velocity and yaw rate. Wenzel et al. (2006) capitalized on the same principle and proposed a dual extended kalman filter for estimating both vehicle state and parameters. Both approaches perform an averaging estimation.

Powertrain Dynamics Fremd (1987) patented a method for determining the mass of a vehicle by recognizing that the first natural frequency of the transmission line, also called the shuffle frequency, is directly linked to the vehicle mass when the transmission ratio is fixed.

Suspension Dynamics The problem of mass estimation is relatively simplified when suspension displacement sensors are available on the vehicle. Kim and Ro (2000) have demonstrated the use of quarter-car suspension models for mass estimation. Rajamani and Hedrick (1995) and Yu and Crolla (1998) capitalized on the same principle for the development of an adaptive observer for suspension states and parameters.

Combinatory Approach All of the above mentioned estimation procedures require a specific driving scenario for enabling an accurate estimation. Either the underlying dynamic model is only valid under certain operation conditions (e.g. a steering maneuver will disturb an algorithm based purely on longitudinal dynamics), or the estimation might suffer from lack of persistent excitation (e.g. in case of an algorithm based on lateral dynamics). Therefore Han et al. (2009) proposed an estimation procedure that combines two sub-estimators, based respectively on longitudinal and lateral dynamics, by using the recursive least-squares method, enabling them to estimate the vehicle mass under a variety of driving conditions.

2.2 Moments of Inertia Estimation

The accurate knowledge of the vehicle's inertia tensor has importance for different applications. In yaw stability control, obviously the yaw inertia will be a crucial system parameter. Most commonly, this vehicle parameter is estimated using a model for the lateral dynamics of a vehicle, as presented by Wenzel et al. (2006).

The roll and pitch moment of inertia are typically more used in (semi-)active suspension control systems and rollover warning systems. Ryu et al. (2002) proposed a least squares method for estimating the roll parameters (inertia, stiffness, and damping) using a two-antenna GPS receiver combined with an Inertial Measurement Unit (IMU). Bolhasani and Azadi (2004) suggested the use of a genetic algorithm to estimate these roll parameters. Rozyn and Zhang (2010) proposed an estimation methodology based on modal analysis techniques, that identifies the sprung mass natural frequencies, damping ratios, and mode shapes. This information is combined with a simplified vehicle model, a least squares analysis, and known equivalent suspension stiffness to estimate the inertial parameters.

Persistency of excitation is also a crucial aspect for this matter: Ryu mentions that normal driving conditions do not excite the vehicle rolling dynamics enough to allow an accurate estimation of the roll inertia.

2.3 COG Position Estimation

The research on COG position estimation is mainly focused on the vertical position of the COG, driven by the importance of this factor in roll-over avoidance. Solmaz et al. (2008) presented an online COG estimation algorithm based on the multiple model switching and tuning methodology. As mentioned in that paper, not too many algorithms exist for an online estimation of the COG height.

3. INNOVATIVE ALGORITHM FOR VEHICLE INERTIAL PARAMETER ESTIMATION

This section introduces an innovative algorithm for estimating the vehicle inertial parameters. The algorithm was originally developed to be used in an active suspension system and therefore assumes the availability of suspension displacement sensors. Using the suspension stiffness characteristics, the mass of the vehicle and the position of the COG in the horizontal plane, can easily be determined. Based on this information, a Monte Carlo method will distribute the payload mass over the different passenger positions in the vehicle. Using anthropometric data sets, it is possible to relate the mass of a passenger to its inertial parameters and COG position. By combining this information with K&C measurements for the empty vehicle, one can obtain the inertial properties and COG position of the loaded vehicle. Fig. 1 shows the overall structure of the presented estimation procedure.

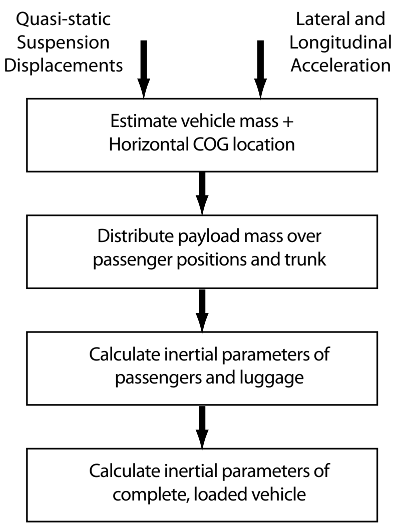

Fig. 1. Overall architecture of the procedure for online estimation of vehicle inertial parameters

Table 1. Overview of observed variables and estimated vehicle inertial parameters

Observed Variables		Estimated Parameters	
Longitudinal acc.	$[m/s^2]$	Total mass	$[kg]$
Lateral acc.	$[m/s^2]$	COG position	$[m]$
Suspension displacements	$[m]$	Principal moments of inertia	$[kg.m^2]$

3.1 Vehicle Mass and Horizontal COG Position Estimation

The problem of estimating the vehicle mass and its horizontal COG position is substantially simplified by the availability of suspension displacement sensors: using accurate suspension stiffness characteristics, the displacements can be related to the suspension forces that are supporting the vehicle mass.

As the vehicle mass does not change rapidly during operation, only the low-frequency content of the displacements is required. The required filtering is achieved by applying a second-order low-pass Butterworth filter with a cut-off frequency of 0.3Hz, based on a simulation based optimization for different road profiles.

The vehicle model that is used for estimating the COG position in the horizontal plane is illustrated in figure 2. For simplicity, the effect of road grade and banking is neglected. The location of the COG in the horizontal plane results from the moment balance equations (1) and (2):

$$(F_{RL} + F_{RR}) \cdot WB - m \cdot a_x \cdot COG_Z - m \cdot g \cdot COG_X = 0 \quad (1)$$

$$(F_{FL} + F_{RL}) \cdot TW + m \cdot a_y \cdot COG_Z - m \cdot g \cdot (TW/2 + COG_Y) = 0 \quad (2)$$

where F_{ij} represents the force at the front(i=F)/rear(i=R) and the left(j=L)/right(j=R) side, WB is the wheelbase, TW is the trackwidth, m is the vehicle mass, a_x and a_y are respectively the longitudinal and lateral acceleration, and COG_k indicates the k-coordinate of the COG position, measured with respect to the center point of the front axle. The COG height, used in these equations, is initialized with a reasonable value and updated with the result of the final COG position estimation.

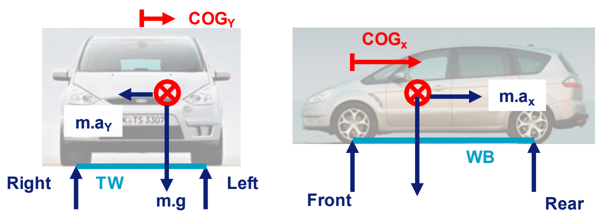

Fig. 2. Simplified vehicle model for estimating the COG location in the horizontal plane

By comparing the mass and COG position for the loaded vehicle and the measurement data for the empty vehicle, it is straightforward to calculate the mass and COG position of the vehicle's total payload.

3.2 Mass Distribution Estimation

The following step in the estimation procedure is distributing the payload mass m_p over the different positions in the vehicle, also referred to as mass allocation points. In the presented research, only the 5 passengers and luggage have been considered; including the fuel tank would be a simple extension. The mass distribution problem arises from the fact there are only 3 equations relating 6 unknown masses m_i, to be allocated to position i:

$$\sum_{i=1}^{6} m_i = m_p \tag{3}$$

$$\sum_{i=1}^{6} m_i \cdot x_i = m_p \cdot x_p \tag{4}$$

$$\sum_{i=1}^{6} m_i \cdot y_i = m_p \cdot y_p \tag{5}$$

This underdetermined system is solved by means of a statistical Monte Carlo method [Metropolis and Ulam (1949)]. The fundamental idea is to assign a probability distribution function (PDF) to every mass allocation point. The Monte Carlo method will randomly sample the variable space and will perform a multitude of experiments to calculate the final result.

The flowchart of one Monte Carlo experiment is illustrated in figure 3. The method will randomly select a mass value for three allocation points from the corresponding PDF. The set of equations (3-5) can now be solved for a unique solution. The total probability of this mass configuration can be calculated by using the PDFs to compute the probability of every individual mass allocation.

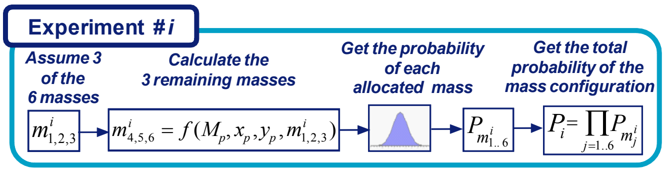

Fig. 3. Flowchart of a single Monte Carlo experiment

The Monte Carlo method will randomly explore the full variable space, resulting in a high number of experiments, each with a corresponding probability. The final mass distribution is simply selected as the result of the experiment with the highest probability.

Figure 4 represents the PDFs for the different mass allocation points. For all positions, a normal distribution was used: the mean and variance value of the main passenger positions correspond to a 50th percentile male dummy, which represents the average male population. A specific PDF is associated with the case where no passengers are located at the rear positions.

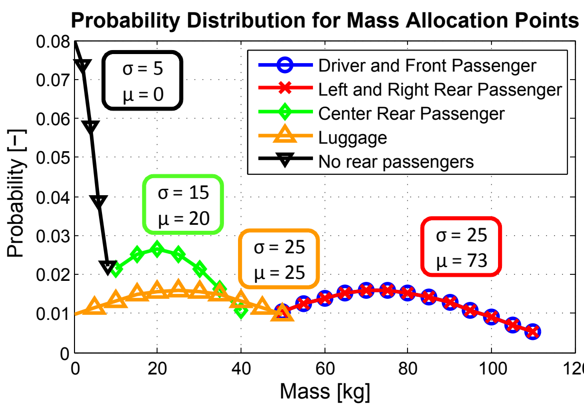

Fig. 4. Probability distribution functions for the different mass allocation points.

Monte Carlo methods are generally associated with a high computational effort. However, by an appropriate selection of the feasible subsets of the variable space, the computational cost can be efficiently limited. As a consequence, the complete algorithm is currently able to estimate the vehicle inertial parameters at a rate of 1Hz.

3.3 Passenger Inertia Estimation

The inertial properties of a passenger are influenced by many uncontrollable variables: the hand or feet position, seat positioning, clothing, gender, etc. In order to enable an estimation procedure, the following assumptions have been made, based on sensitivity analyses performed in LMS Virtual.Lab Motion:

- Driver and passenger are both seated with their hands on the thigh. Compared to a normal driving position, the difference in COG height is limited to 2%.
- Passenger COG positions are fixed with respect to the seat. Comparison between the results for a 1.75m and 2m tall person, shows a difference in COG location of less than 1%.
- Only the principal moments of inertia are considered.
- The relationship between a person's mass and his/her stature is expressed by a fixed body mass index of 23, which is representative for the average male population.

The COG positions of the different body parts are obtained from a technical report from the Transportation Research Institute of the University of Michigan that presents the anthropometric specifications of a mid-sized male dummy, as illustrated in figure 5 [Robins (1983)].

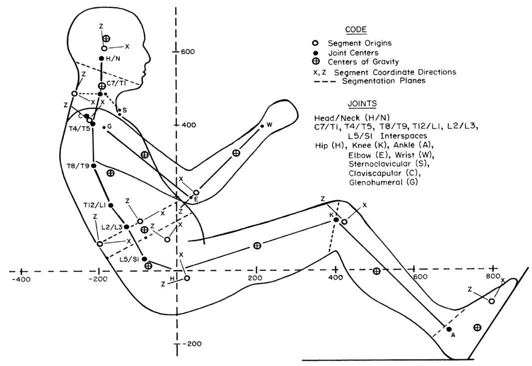

Fig. 5. Anthropometric specifications for mid-sized male dummy. [Robins (1983)]

Based on experimental data, Zasiorsky and Seluyanov (1983) have derived regression coefficients relating the inertial properties of every body part to a person's body mass and stature. Using this data in combination with the body parts' COG position results in an accurate estimation of a passenger's inertia tensor.

Regarding the luggage, it is a reasonable assumption to consider this as a solid cuboid with fixed volume, resulting from the trunk dimensions, and varying mass. The horizontal COG position is fixed, while the COG height varies linearly with the mass allocated at the luggage position.

3.4 Full Vehicle Inertial Properties Estimation

All passengers' inertial properties can be combined in one payload inertia tensor by using the parallel axis theorem, based on information on the positioning of the different seats. An identical procedure is used to combine these payload inertial properties with those of the empty vehicle, resulting in an estimation of the loaded vehicle's moments of inertia and COG position.

4. VALIDATION

The presented estimation procedure is validated by means of a K&C measurement campaign. Different loading configurations can be simulated by putting dummy passengers in the vehicle. The steady-state suspension forces and suspension displacements can be measured on the testrig.

In the considered test configuration, dummy passengers are located at the driver position and the front-right and rear-left passenger position, resulting in an extra payload mass of 210 kg. Tabel 2 compares the estimated values for the COG position and the moments of inertia with the measurement data. It must be noted that the relative error for the COG_Y position was evaluated with respect to the half trackwidth.

The high accuracy of the estimation procedure is reflected in the relative estimation errors, which are limited to about 1-2%.

The same validation procedure has been repeated for several other loading configurations, listed in table 3. The results are summarized in table 4, which shows the absolute and relative estimation error for each loading configuration. It can be concluded that the proposed estimation algorithm provides very accurate estimations of the vehicle inertial parameters.

Table 2. COG Position and moments of inertia for test configuration

	$COG_X(mm)$	$COG_Y(mm)$	$COG_Z(mm)$
Measurement	1246	-13.7	572.5
Estimation	1243	-24.3	579.2
Absolute Error	-3	-10.6	+6.7
Relative Error	-0.3%	-1.4%	+1.2%
	$I_{XX}(kg \cdot m^2)$	$I_{YY}(kg \cdot m^2)$	$I_{ZZ}(kg \cdot m^2)$
Measurement	796	3586	3885
Estimation	805	3540	3842
Absolute Error	+9	-46	-43
Relative Error	+1.1%	-1.3%	-1.1%

Table 3. Loading Configurations for Estimation Procedure Validation

Configuration	Description
Conf. A	Driver
Conf. B	Driver + Luggage
Conf. C	Driver + FR Passenger
Conf. D	Driver + FR Passenger + RL Passenger
Conf. E	Driver + FR Passenger + 3 Children
Conf. F	Driver + FR Passenger + 3 Children + Luggage

Table 4. Evaluation of estimation accuracy for different loading configurations: Absolute and relative error for COG positions and moments of inertia

Configuration	COG_X (mm) Abs.	Rel.(%)	COG_Y (mm) Abs.	Rel.(%)	COG_Z (mm) Abs.	Rel.(%)
Conf. A	9.2	0.8	8.9	1.1	3.8	0.7
Conf. B	5.1	0.4	8.2	1.0	0.1	0.0
Conf. C	18.3	1.5	13	1.7	7.1	1.2
Conf. D	-3.6	-0.3	10.6	1.4	6.7	1.2
Conf. E	2.4	0.2	12.3	1.6	-2.7	-0.5
Conf. F	0.3	0.0	11.6	1.5	5.7	1.0
Configuration	I_{XX} $(kg \cdot m^2)$ Abs.	Rel.(%)	I_{YY} $(kg \cdot m^2)$ Abs.	Rel.(%)	I_{ZZ} $(kg \cdot m^2)$ Abs.	Rel.(%)
Conf. A	1.5	0.2	-1.8	-0.1	6.1	0.2
Conf. B	7.1	0.9	2.6	0.1	6.6	0.2
Conf. C	9.1	1.2	-5.5	-0.2	8.6	0.2
Conf. D	8.6	1.1	-46.3	-1.3	-43.4	-1.1
Conf. E	15.5	1.9	12.6	0.3	9.1	0.2
Conf. F	35.7	4.5	-74.1	-2.0	-66.1	-1.6

The presented estimation algorithm has been successfully adopted in the control algorithm for a hydraulic active suspension system. De Bruyne et al. (2011) present the architecture of the control algorithm, the development of an accurate state estimator, and evaluate the improved system performance.

5. CONCLUSION

In this paper, an innovative algorithm is presented for the online estimation of the inertial properties of a road vehicle. As these inertial parameters substantially influence the longitudinal, lateral and chassis dynamics of a vehicle, the availability of an accurate estimate could significantly improve the performance of the corresponding control systems. Most of the reported estimation algorithms capitalize on this sensitivity of the dynamics for a certain inertial property, but require, as a consequence, a persistent level of dynamic excitation to ensure a correct estimation.

The algorithm presented in this paper was originally developed to be adopted in an active suspension system and therefore assumes the availability of suspension displacement signals. The low-frequency content of these displacements is combined with suspension stiffness characteristics, resulting in an estimation of the vehicle mass and the COG position in the horizontal plane. A Monte Carlo method uses probability distribution functions for the different mass allocation points to calculate the payload mass distribution. Based on the weight assigned to a passenger, anthropometric data sets permit to calculate the inertial properties of each passenger, eventually resulting in the inertial properties of the full, loaded vehicle. Comparing the results from the presented estimation algorithm with accurate K&C measurement data for different loading configurations, shows that this innovative procedure can estimate the inertial properties within an accuracy of about 2%.

The independence of persistent dynamic excitation and the high estimation accuracy, enabled the successful adoption of this online estimation procedure in the control algorithm of an active suspension system.

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