Online estimation of tire normal force with applying hardware-software couple model

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ABSTRACT

Tire online normal force has effects on vehicle safety and performance and dynamic control systems. It is influenced by too many parameters such as vehicle mass and center of gravity (CG) position and vehicle instantaneous dynamics states. In this paper, a new estimation algorithm is developed to estimate tires' online normal forces during a maneuver. The proposed algorithm uses a dynamic measure module to make a hardware-software coupled model which is validated by real test data. The algorithm uses artificial neural networks advantages to estimate the vehicle mass distributions. A combination of real and model-generated data is used to train, test, and validate the artificial neural network structure. By applying two roll and pitch artificial neural network blocks, it estimates tires' static normal forces. In this respect, the validated vehicle model instantaneously monitors the estimated values. The results show that the proposed algorithm estimates the vehicle total mass with less than 5 percent. In addition, the coupled model uses the estimated static values to estimate the tire's online normal forces with considering the measured vehicle dynamics states by dynamic module. Comparing the obtained results from the proposed method with the outputs from Carsim indicates the acceptable accuracy of this method.

KEYWORDS

Mass estimation, Artificial neural network, Roll and pitch dynamics, Online tire force

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Introduction

Nowadays with vehicles promotion, many types of vehicle dynamic control systems (VDCS) are promoted. The VDCSs are trying to enhance vehicle safety, performance, ride, and comfort. Most of these systems are model-based [1–2]. VDCS performance depends on the control algorithm, vehicle model, and exactness of the vehicle parameters. Different models with different degrees of freedom (DOF) have been proposed to simulate vehicle dynamic behaviors [3–4]. Control algorithms need vehicle parameters and states to produce an effective control effort. One of the important parameters for vehicle dynamic control systems such as ESP, ABS, and TCS is the normal force on the tire which depends on vehicle dynamic states, vehicle mass, road grade, and the CG position. Vehicle mass estimation can be done by considering vehicle longitudinal dynamics by calculating or measuring wheels torques [5-7]. This method depends highly on the accuracy of the measured/calculated wheels torques. However, High-tech systems and the motor map are required to measure and estimate the wheel's torques [8]. Despite vehicle mass, the CG position is so important to estimate normal forces. For vehicle dynamic controllers and safety systems, in this regard, a novel algorithm is proposed to estimate the vehicle mass, CG position, and road grade angle. The algorithm utilizes an ANN for roll dynamic and yaw dynamic blocks, each of which is trained, tested, and validated with experimental data set. Besides, a threshold algorithm determines the vehicle maneuver based on IMU data to active one of roll block ANN or yaw block ANN. Each of the yaw and roll blocks runs with IMU data to estimate related mass distribution in each related side.

2- Modeling

To design the algorithm, a 9-DOF coupled vehicle model is proposed and experimentally validated using MATLAB/Simulink environment. It consists of roll, pitch, lateral, longitudinal, and 5 vertical dynamic sub-models. Vehicle CG inertial accelerations are [8]:

$$\ddot{x}_{inertial} = \ddot{x} - rv \tag{1}$$

$$\ddot{y}_{inertial} = \ddot{y} + ru \tag{2}$$

while the $\ddot{x}$ and $\ddot{y}$ are absolute vehicle longitudinal and lateral acceleration, $\ddot{x}_{inertial}$ and $\ddot{y}_{inertial}$ are the total longitudinal acceleration in CG position, r is the yaw rate and u and v are the longitudinal and lateral velocity of the vehicle. Vertical dynamic with gyroscopic effects is formulated as follow [8]:

$$\begin{aligned}
&m_s(\dot{z}_s - uq + vp) - m_s h_s(q^2 + p^2) + m_s c_s rp \\
&+k_{sFL}(z_{sFL} - z_{uFL}) + k_{sFR}(z_{sFR} - z_{uFR}) \\
&+k_{sRL}(z_{sRL} - z_{uRL}) + k_{sRR}(z_{sRR} - z_{uRR}) \\
&+c_{sFL}(\dot{z}_{sFL} - \dot{z}_{uFL}) + c_{sFR}(\dot{z}_{sFR} - \dot{z}_{uFR}) \\
&+c_{sRL}(\dot{z}_{sRL} - \dot{z}_{uRL}) + c_{sRR}(\dot{z}_{sRR} - \dot{z}_{uRR}) = 0
\end{aligned} \tag{3}$$

where m_s is the sprung mass, h_s is the sprung mass CG position to the ground, c_s the distance between vehicle CG position and sprung mass CG position, p and q are roll rate and pith rate, $\dot{z}_s$ is the vertical velocity of sprung mass, k_{si} and c_{si} are the suspension's stiffnesses and damping, z_{si} and z_{ui} are the sprung mass and unsprung mass displacements and $\dot{z}_{si}$ and $\dot{z}_{ui}$ are the related velocities $(i = FL, FR, RL, RR)$. The unsprung mass displacement can be obtained from pitch and roll angle:

$$z_{sFL} = z + \phi c_{FL} - \theta l_F \tag{4}$$

$$z_{sFR} = z - \phi c_{FR} - \theta l_F \tag{5}$$

$$z_{sRR} = z - \phi c_{RR} + \theta l_R \tag{6}$$

$$z_{sRL} = z + \phi c_{RL} + \theta l_R \tag{7}$$

while ϕ and θ are roll and pitch angle, c_i is the lateral distance of CG position to related wheels and l_F and l_R are the longitudinal distances of CG to front and rear axles.

Hence, vertical dynamics for unsprung masses are according to the below functions [8]:

$$m_{uFL}\ddot{z}_{uFL} - c_{sFL}(\dot{z}_{sFL} - \dot{z}_{uFL}) - k_{sFL}(z_{sFL} - z_{uFL}) + F_{zdFL} = 0 \tag{8}$$

$$m_{uFR}\ddot{z}_{uFR} - c_{sFR}(\dot{z}_{sFR} - \dot{z}_{uFR}) - k_{sFR}(z_{sFR} - z_{uFR}) + F_{zdFR} = 0 \tag{9}$$

$$m_{uRL}\ddot{z}_{uRL} - c_{sRL}(\dot{z}_{sRL} - \dot{z}_{uRL}) - k_{sRL}(z_{sRL} - z_{uRL}) + F_{zdRL} = 0 \tag{10}$$

$$m_{uRR}\ddot{z}_{uRR} - c_{sRR}(\dot{z}_{sRR} - \dot{z}_{uRR}) - k_{sRR}(z_{sRR} - z_{uRR}) + F_{zdRR} = 0 \tag{11}$$

while m_{ui} are unsprung masses and the normal forces on tires, F_{zdi} are as:

$$\begin{aligned}
F_{zdFL} &= -\left(\frac{h_F m_s}{L}\frac{c_{FR}}{T_F}(\ddot{x} + g\sin(\alpha) - rv)\right) \\
&+\left(\left(\frac{hm_s}{T_F}\frac{l_R}{L}\right)(\ddot{y} + ru)\right)
\end{aligned} \tag{12}$$

$$\begin{aligned}
F_{zdFR} &= -\left(\frac{h_F m_s}{L}\frac{c_{FL}}{T_F}(\ddot{x} + g\sin(\alpha) - rv)\right) \\
&-\left(\left(\frac{hm_s}{T_F}\frac{l_R}{L}\right)(\ddot{y} + ru)\right)
\end{aligned} \tag{13}$$

$$F_{zdRL} = (\frac{h_R m_s}{L}\frac{c_{RR}}{T_R}(\ddot{x} + g\sin(\alpha) - rv)) + ((\frac{hm_s}{T_R}\frac{l_F}{L})(\ddot{y} + ru)) \quad \textbf{(14)}$$

$$F_{zdRR} = (\frac{h_R m_s}{L}\frac{c_{RL}}{T_R}(\ddot{x} + g\sin(\alpha) - rv)) - ((\frac{hm_s}{T_R}\frac{l_F}{L})(\ddot{y} + ru)) \quad \textbf{(15)}$$

where L is the vehicle wheelbase, g in the gravity, α is the road slope, T_F and T_R are the vehicle front and rear wheel tracks. The roll and pitch dynamics are according to the below equations. Lastly, the tire normal force can be obtained by using below equations:

$$F_{zFR} = (\frac{mg\ \cos(\alpha)\ l_R}{L}\frac{c_{FL}}{T_F}) + F_{zdFR} \quad \textbf{(16)}$$

$$F_{zFL} = (\frac{mg\ \cos(\alpha)\ l_R}{L}\frac{c_{FR}}{T_F}) + F_{zdFL} \quad \textbf{(17)}$$

$$F_{zRL} = (\frac{mg\ \cos(\alpha)\ l_F}{L}\frac{c_{RR}}{T_R}) + F_{zdRL} \quad \textbf{(18)}$$

$$F_{zRR} = (\frac{mg\ \cos(\alpha)\ l_F}{L}\frac{c_{RL}}{T_R}) + F_{zdRR} \quad \textbf{(19)}$$

where, F_{zi} are instant normal forces of tires. As the equations show, to achieve real-time exact normal force, the real vehicle mass, CG position, body dynamics states, and road slop are required. In this paper a solution proposed for each of them.

Hardware-software couple model:

To achieve the goal of this paper, a high accuracy model is needed. Since the major uncertainty source in vehicle modeling is tire-road interaction, a new Hardware-software developed to eliminate the uncertainty sources. The hardware measures the tire-road reactions by measuring the body accelerations directly. The hardware is a dynamics module that can be coupled with the abovementioned equations to have a complete vehicle model without considering tire-road interactions.

The hardware which is used for this purpose was a GPS/IMU module. The filters applied to the sensor signals as the pre-processing phase are as follows: Complementary filter, Kalman filter [9] are internal device filters and Wavelet function (sym5, level 4 (and Lowpass butterworts filter (10 Hz) . To verify the model and the simulation, an ISO Double-lane Change maneuver was performed. The test vehicle was Runna IKCO.

Accordingly, the developed model can accurately predict the experimental measurement with a little time delay. The main culprits for the generated delays are the applied filters, especially the Low-pass butterworts filter (10 Hz). One of the most important points in using IMU/GPS hardware is installation and adjustment. The hardware is installed at a point pretty much close to the curb CG, and the sensor axis must observe the vehicle CG states in vehicle coordinate. Since usually the axes are not in exact coordinates, two steps are followed to explain the procedure of axis adjusting. The first step is adjusting the z-axis which is perpendicular to the ground. When the vehicle is on a level surface and in a standstill model the z acceleration should be equal to the local gravity value. The second step is adjusting and rotating the axis to vehicle coordinate. For this purpose, the car was driven slowly in a straight line and level road. With this method, all accelerations in XY plane, must be in x-direction. Finally, the axes overlap the vehicle CG coordinate system.

Vehicle mass and CG position estimation:

The selected method to estimate the vehicle parameters is to take advantage of ANNs. ANNs are powerful, nonlinear interpolators that benefit from real input-output datasets. However, when working with ANNs, it is of real importance to choose an appropriate structure and a training method. In this paper, a multi-layer perceptron (MLP) ANN structure is used to estimate the distribution of vehicle mass with regarding two roll and pitch ANN blocks. Due to the large size of the dataset and a shortage of data in comparison to the whole operating range, there is a high tendency to over-fitting in training procedures. In order to avoid over-fitting and increase the network generalization, Bayesian regularization method is used for training the network. The Bayesian method is a probabilistic method that takes into account both the network architecture and estimation error while training. A sophisticated study on the Bayesian training method has done [10]. A two layers ANN with 10 neurons in each hidden layer is used for estimation parameters. These structures have been selected by trial and error.

Obviously, an ANN needs a dataset to be trained, validated, and tested. The dataset used in here is composed of both generated data from the experimentally validated couple model in addition to real, experimental data. The ANN dataset for roll consists of extremum vehicle roll angle, lateral acceleration, and weight loads, which are positioned in predetermined vehicle seat points. The ANN dataset for pitch, on the other hand, consists of extremum vehicle pitch angle, longitudinal acceleration, and weight loads which are positioned in predetermined vehicle seats. 70 % of the dataset is assigned for training, 15% for validation, and 15 % for testing. To create data, it is assumed that passengers are positioned in the default position and the default driver weight is 60 kg. Additional driver and passengers' weights have possible variations. With this regard, the vehicle total mass, the distributions, and vehicle moment of inertia can be achieved. To generate training data, the initial inputs are a_y and a_x are created in such a manner that happens in real maneuvers. As mentioned before, the training data is composed of a generated dataset and a real one. The real data is sin input maneuvers with different passenger load situations. In this regard, all requirements for tire normal force calculation were achieved.

Results and Discussion

To validate the algorithm, a vehicle maneuver with increasing amplitude sin inputs is performed while the vehicle is accelerating and decelerating repeatedly. The passengers' masses and which are positioned in the rear left and front left.

After the algorithm execution, the pre-processed data can estimate the vehicle mass distribution. The results obtained reveal that the developed algorithm is capable of predicting the vehicle parameters with an overall error of less than 5%. It might be interesting to note that an even more accurate estimate can be achieved by carrying on the maneuver further. With the estimated parameters and dynamics states which had been measured by the dynamics module, tire online normal forces were achieved. The estimated values compared with pre-validated Carsim model results. Figure 2 shows the estimated values are very accurate.

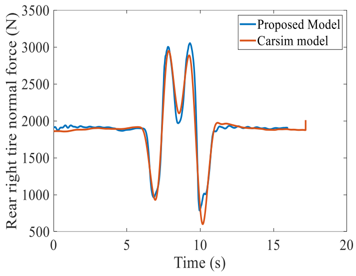

Figure 2: comparing the proposed estimation method results with pre-validated Carsim model results

Conclusion

In this paper, a novel algorithm is proposed to estimate tires' online normal forces. For this reason, a novel couple model was introduced to decrease the algebraic models' uncertainties and make accurate vehicle dynamics states accessible. For estimating vehicle mass and CG position two ANN blocks were trained and optimized to estimate vehicle mass and its distribution. The algorithm used the developed couple model and the ANN roll and pitch blocks to calculate the tire's normal forces. According to the results obtained, the proposed method estimates the parameters with less than 5% error, and the estimated online normal forces were close to pre-validated Carsim model results.

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