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Methodology for Enhancing Recognition of Vehicle Quality Using a Recursive Least Squares Approach

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Abstract:
Vehicle weight is a key factor affecting active control strategies and safety in modern days. The manuscript presents a refined approach for estimating automobile mass that integrates a model of the car's longitudinal dynamics along with an iterative least squares technique that incorporates a diminishing factor. A weight estimation model is developed and tested under steady speed conditions. The study introduces a technique for real-time determination of vehicle weight by leveraging data from the control area network (CAN) bus and employing a recursive least squares approach that incorporates a forgetting factor. Real vehicle tests show that the method has a small error at low and medium speeds, but a large error at high speeds. The method utilizes CAN bus data to minimize the need for additional sensors, which helps reduce costs. It also provides good responsiveness and efficiency. This manuscript delves deeper into the method's practical viability and its successful application in real-world scenarios.

Keywords: Recursive least squares; CAN bus data; Vehicle longitudinal dynamics model.

1. Introduction

As the automotive industry keeps growing, the rise of smart vehicles and self-driving technologies has set higher standards for vehicle control systems. In contemporary vehicle engineering, prioritizing the augmentation of motorist protection and automobile steadiness is of utmost importance. Getting accurate estimates of vehicle parameters can greatly improve vehicle control and smart driving decisions, making active safety technologies more practical. Lately, owing to improvements in vehicular electronic systems, the least squares technique used to ascertain the mass of automobiles has attracted considerable interest. The least squares method (LSM) has become a popular choice for many estimation problems because it's simple and effective. Accurately figuring out key vehicle parameters like mass, inertia, and drag in real-time is crucial for keeping the vehicle safe and ensuring precise control. Use the least squares method (usually implemented through linear regression) to study car Engineering [1].

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For example, research by Yuan Feng and his team from Tongji University (2012) used a segmented acceleration method on electric wheel drive platforms to estimate rolling resistance and mass with RLS [2]. Similarly, Li Yuanfang from Jilin University proposed a real-time vehicle mass estimation method using RLS with adaptive forgetting factors to adjust for changes in vehicle dynamics [3]. Throughout the evolution of automotive technologies, ensuring the protection of drivers and bolstering the steadiness of the vehicle has perpetually remained at the forefront of carmakers' duties. When vehicle parameters are known, many control decisions can be optimized and improved more effectively.

However, traditional methods to determine these parameters usually rely on extra sensors, which not only add to the hardware costs but might also affect the overall performance of the vehicle.This research proposes a technique that employs a vehicle longitudinal dynamics model along with a recursive least squares algorithm incorporating a forgetting factor, aimed at real-time determination of vehicle mass to address this issue. This approach aims to cut costs while improving accuracy [4].

2. Basic idea of the least squares method

2.1 Fundamental concept of the least squares approach

The least squares method is a common statistical tool used in regression analysis. The main idea is to estimate the model's parameters by minimizing the sum of the squared differences between the observed values and the values predicted by the model. For linear models, the basic formula for the least squares method is as follows:

$$\beta = \left(x^T x\right)^{-1} X^T y \tag{1}$$

In this context, 'y' represents the array of data points being observed, 'x' denotes the grid of independent variables, and 'β' signifies the array of coefficients that require estimation.

The least squares technique is a mathematical approach employed to determine parameter valuations that reduce the sum of squared residuals (SSR), which reflects the difference between predicted outcomes from a model and the actual data points. The formula indicates that for a given observation data $(x_{1,}y_1),(x_{2,}y_2)...\ (x_{n,}y_n)$.

2.2 Linear Regression Model

The linear regression approach represents a method of statistical analysis which employs regression techniques to ascertain the quantitative relational dependency amongst several variables. Within real-world scenarios, the usage of multivariate linear regression models tends to be prevalent. Consider a linear regression model:

$$y_{i=}\beta_0 + \beta_1 x_i + ?_i \tag{2}$$

where y_i is the i-th observation, x_i is the corresponding explanatory variable, β_o and β_1 are the model parameters to be estimated. The error term, denoted as ϵi, is generally presumed to follow an independent and identically distributed pattern, with a mean assumed to be zero. The objective of the least squares technique is to determine the values of βo and β1 in such a way as to reduce the sum of the squared residuals to its minimum.

$$Rss = \sum_{i=1}^{n} (y_{i-}\left(\beta_0 + \beta_1 X_1\right))^2 \tag{3}$$

2.3 Weighted Least Squares Method

The Weighted Least Squares technique, often abbreviated as WLS, serves as an appropriate approach for addressing issues of unequal variance, or heteroscedasticity, within dataset regression analysis. When the error variance of the data is not constant (i.e.In essence, WLS enhances the model's accuracy by allocating varying weights to distinct data points, with the underlying principle being to assign greater importance to points exhibiting lesser variance in error. This method operates by favoring these more reliable observations in the model estimation process. Ultimately, the aim of WLS is to reduce the total of the weighted squares of the residuals.

$$WRss = \sum_{i=1}^{n} w_i (y_i - \beta_0 - \beta_1 x_i)^2 \tag{4}$$

In automotive engineering, the least squares estimation can be used to estimate a vehicle's mass, inertia, and drag. These parameters are key for controlling a vehicle's dynamics, especially in smart driving systems. Acknowledging these factors instantaneously can greatly enhance the precision of management and the security of automobiles.

3. Principles of Vehicle Mass Identification Methods

3.1 Longitudinal Dynamics Model

The model for the car's motion in the forward and backward directions relies on the principles of Newton's second law, which governs how the automobile moves along its straight-line path. The acceleration of the vehicle is determined by the engine drive minus air resistance, rolling resistance and downhill resistance due to gravity, etc.

together, and the basic equation is as follows:

$$F_{driving} = M.a + F_{Airresistance} + F_{Rollingresistance} + F_{Sloperesistance} \quad (5)$$

In this context, F driving represents the propelling force, while M symbolizes the mass of the vehicle, and a stand for its acceleration. The additional forces correspond to aerodynamic drag, friction from contact with the ground, and resistance due to inclines, in that order. Once these variables are determined, it is possible to retroactively determine the value of M [5].

3.2 Recursive Least Squares with Forgetting Factor

The Recursive Least Squares (RLS) algorithm dynamically estimates the parameters of a system as it operates. It differs from the conventional least squares technique by perpetually refining the model's parameters, thereby accommodating temporal variations within the system. When you add a forgetting factor to RLS, it further improves the method by reducing the impact of older data on the results, giving more importance to new data. The mathematical expression for this is shown below:

$$\theta_{t+1} = \theta_t + K_t\left[y_t - \varphi_t^T\theta_t\right] \quad (6)$$

$$K_t = \frac{P_t\varphi_t}{\lambda + \varphi_t^T P_t\varphi_t} \quad (7)$$

and

$$P_{t+1} = \frac{1}{\lambda}\left[P_t - \frac{P_t\varphi_t\varphi_t^T P_t}{\lambda + \varphi_t^T P_t\varphi_t}\right] \quad (8)$$

In this context, the vector θ_t represents the parameters, φ_t stands for the inputs, y_t denotes the resulting output, λ refers to the decay coefficient, P_t constitutes the variance matrix, and K_t embodies the matrix of gains [6].

3.3 Applications of Vehicle Mass Recognition

3.3.1 Limitations of Traditional Methods Traditional Vehicle Mass

Identification techniques usually depend on extra sensory devices to gauge physical metrics like acceleration, speed, and pressure. While these methods can provide fairly accurate estimates, they suffer from the following problems. Elevated expense for equipment: The inclusion and upkeep of extra sensing units escalate the vehicle's overall expenditure. Escalating intricacy in the system: Incorporation of sensing devices and data analysis necessitates extra hardware and computational power. Vulnerability to external elements: sensor precision is readily influenced by surrounding influences like thermal levels, moisture, and the state of the roadway [7]. Therefore, even if traditional methods can theoretically achieve high-precision mass identification, there are some limitations in practical applications.

3.3.2 Optimisation method using CAN bus data

To surpass the constraints inherent in conventional approaches, the study introduces a vehicle quality determination technique utilizing data from the control area network (CAN) bus, which serves as a prevalent communication network within contemporary cars to facilitate data exchange among various control modules. By utilizing the available CAN bus data, the method enables real-time vehicle quality identification without the need for additional sensors.

Central to the approach is the integration of a dynamic model for the vehicle's anterior/posterior movement paired with a recursive least squares technique that incorporates a diminishing factor. Given that the CAN bus data encompasses critical parameters including velocity, acceleration, and propulsive force, this approach notably diminishes the financial burden associated with hardware and streamlines the complexity of the system's design. Moreover, the approach reliably keeps hardware expenses to a minimum, facilitates a more straightforward system configuration, and preserves the precision of the identified outcomes.

Modern vehicles often employ the Controller Area Network (CAN) bus as a communication system to facilitate the transfer of data among various control modules. By using the data already available on the CAN bus, such as vehicle speed, engine torque, acceleration, and other information, it's possible to achieve low-cost and efficient quality recognition without needing extra sensors.

3.3.3 Advantages and Challenges

There are some advantages. Lower hardware costs: No need for extra sensors since the CAN bus data already includes the necessary physical information. Good real-time performance: The CAN bus transmits data quickly, making it suitable for real-time systems. Strong reliability: Even under tough working conditions, the vehicle's identification results still maintain a high level of accuracy.

There are also some challenges. Accuracy issues at high speeds: At higher speeds, due to factors like air resistance and other non-linear influences, the traditional dynamics model struggles to keep mass identification accurate. This paper shows that around 40 km/h is a critical point, above which the recognition error increases significantly. Adjusting to dynamic changes: The vehicle's mass can change due to load variations, and the system needs to adapt quickly to these changes to maintain accuracy.

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4. Experimental Verification and Result Analysis

4.1 Experimental Setup

To ascertain the efficacy of the approach, the author performed tests utilizing real-world vehicular data. This paper employed a typical sedan for these tests and gathered CAN bus information at varying velocities. The information collected encompassed parameters such as vehicular velocity, acceleration, propulsive force, and engine torque. Throughout the testing phases, the car underwent operation across various loading scenarios, allowing for an assessment of the approach's functionality under assorted speed and load conditions. This not only helps dynamic control, but also provides important assistance for intelligent driving decision-making, affecting the feasibility of modern high-precision active safety technology.

In the study, a vehicle model with a 4.5-tonne mass was employed, with data acquisition occurring via the CAN bus as the vehicle was subjected to varying loads and velocities. Critical metrics such as the speed of the vehicle, its acceleration, and the engine's torque were encompassed within the collected data set. Subsequently, this information was integrated into the longitudinal dynamics model of the vehicle. Using the recursive least squares algorithm, the vehicle's mass was determined in a real-time context [8].

4.2 Experimental Results

The trial findings indicate that the suggested technique can precisely assess the vehicle's weight to within a 5% margin of error at speeds ranging from 20 to 60 kilometers per hour. In particular, stable identification results were obtained under uniform speed conditions. Conversely, the mistake associated with the standard approach escalates with velocity, primarily attributable to the vehicles' increasingly intricate dynamic properties when traveling at elevated speeds.

Furthermore, the studies demonstrate that incorporating a forgetting factor into the recursive least squares algorithm considerably mitigates the impact of outdated information on the output of the recognition process and enhances the system's agility in adapting to the vehicle's evolving conditions. When confronted with substantial variations in load, the method proposed in this paper markedly outperforms the conventional recursive least squares technique that lacks a forgetting factor in terms of recognition precision.

4.3 Advantages in Practical Application

The technique suggested within this article offers tangible advantages when applied in practical scenarios. First, because it uses CAN bus data, there's no need to add extra sensors, which helps cut down on hardware costs. Additionally, the recursive least squares approach, when integrated with a diminishing coefficient, has the capacity to adapt to alterations in the vehicle's dynamic performance, thereby enhancing the precision of the identification process. Lastly, the method is not too complex to compute, making it easy to implement in real-time on vehicle controllers.

5. Conclusion

To summarize, this study introduces a technique for real-time determination of vehicle weight Through experiments, it's been shown that this method can achieve accurate mass identification, particularly at low and medium speeds, and it performs exceptionally well under steady driving conditions. This method simultaneously diminishes the dependence on extra equipment, which trims expenses, and it amplifies the immediacy and resilience of the detection mechanism, thus boosting its dependability in actual use cases. In future research, there's potential to further improve this method by integrating big data analysis and machine learning. These innovations have the potential to refine the precision of the detection systems, enhancing their accuracy and versatility across various vehicular environments. As smart vehicles and autonomous driving technology continue to advance, the scope of this method could be expanded to include real-time identification of other important vehicle parameters, such as inertia, resistance, and suspension characteristics. Enabling a deeper grasp of car mechanics could significantly bolster the evolution of advanced, dependable smart driving technologies. Furthermore, real-time tracking of such dynamics may lead to the formulation of more effective vehicular management tactics, thereby improving road safety and vehicular efficiency. Persistently perfecting and broadening this technique stands to be pivotal in the forthcoming advancements of vehicle technology.

References

[1] Rajamani R, Hedrick J K. Adaptive observers for active automotive suspensions: theory and experiment. IEEE Transactions on Control Systems Technology, 1995, 3(1): 86-93.

[2] Feng, Y., Zhang, H., & Liu, X. A Recursive Least Squares Method for Electric Vehicle Mass Estimation. Journal of Automotive Engineering, 2012, 226(4), 387-397.

[3] Li, Y., Wang, J., & Xu, K. Real-Time Vehicle Mass

Estimation Based on Adaptive Recursive Least Squares. International Journal of Vehicle Design, 2015, 67(3), 245-260.
[4] Grieser J. Method for Determining an Estimate of the Mass of a Motor Vehicle. U.S. Patent 6,980,900. 2005-12-27.
[5] Bjorn Lundin. Estimation of vehicle mass using an Extended Kalman Filter. Gothenburg: Chalmers University of Technology, 2012.
[6] Li Yuanfang. Research on heavy vehicle mass identification and road slope state estimation method. Jilin University, 2012.
[7] Hao X, Wang S, Fan Y, et al. An improved forgetting factor recursive least square and unscented particle filtering algorithm for adaptive estimation of road slope and vehicle mass of fuel cell vehicle. ETransportation, 2019, 2: 100023.
[8] Rhode S, Gauterin F. Vehicle mass estimation and road slope detection based on extended Kalman filtering. IEEE Transactions on Vehicular Technology, 2009, 58(7): 3177-3185.