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Ultra-local model-based observer design for automated vehicles

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Abstract:
This paper presents a novel observer design method that combines the Linear Quadratic (LQ) and ultra-local model-based approaches. Firstly, the LQ observer design is performed, which uses the nominal model of the system. Then, the ultra-local model-based solution is introduced. The results of the LQ observer are augmented with the ultra-local model, which aims to increase the accuracy of the estimation process even for systems with high nonlinearities. During the implementation process, in the nominal observer the parameter uncertainties are not taken into account. These effects are also considered with the application of the ultra-local model. The design process is carried out for an automated vehicle-related observation problem, the lateral velocity estimation. Finally, the whole observer algorithm is implemented in high-fidelity vehicle dynamics simulation software to show its effectiveness.

Keywords: ultra-local model, observer, state estimation, lateral velocity

1. INTRODUCTION AND MOTIVATION

Nowadays, the main focus of the automotive industry is on the development of fully automated, autonomous vehicles. One of the main challenges of autonomous vehicles is their control system, which must guarantee accurate trajectory tracking and the stable motion of the car even in dangerous situations such as emergency lane change or braking. In order to develop a reliable, high-performance-level control algorithm several states of the vehicle must be accurately known. However, some signals, such as the lateral velocity of the vehicle cannot be measured directly or require high-precision, expensive sensors. These devices would make a significant increase in mass production costs thus they should be replaced with other technical solutions.

In the last decades, several algorithms have been developed, which aim to estimate the non-measurable or costly measurable states of the vehicles. These solutions can be divided into two main groups: 1. Model-based estimation algorithms, 2. Data-based solutions.

The first group includes the classical methods, which are based on a mathematical model of the considered system. One of the widespread solutions is the Linear Quadratic (LQ)-based observer design Akbari et al. [2012]. This technique requires a state-space representation of the system, which is given, in general, in LTI form. LQ observers can give a high-performance level when the dynamics of the system are within its linear range. In the case of highly nonlinear systems, such as vehicle systems, other methods can be used e.g., robust techniques ($\mathcal{H}_\infty$, Linear Parameter Varying (LPV)). Using the $\mathcal{H}_\infty$ technique, several parameter uncertainties and the nonlinearities of the system can be handled Chadli et al. [2010]. Moreover, the stability of these algorithms can be proven analytically. However, its performance level drops when the model contains significant nonlinearities.

In order to avoid the modeling process, new techniques started to take place in the field of observers. These solutions make up the second group: the data-driven observers. In general, these methods involve a machine learning algorithm to provide an estimate of the selected signal. For example, a neural network is a widely used technique e.g. Du et al. [2010]. Regression techniques are also suitable for estimation problems Fenyes et al. [2018]. The main advantage of the machine learning methods is that no accurate

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model is needed for the observer design. On the other hand, these techniques require a large amount of data to provide good results and generalization level. However, in some cases, the required data is not available or it does not cover the whole operating range of the system and the parameters of the system can also change during its lifetime. Another pitfall of machine-learning techniques is stability since there is no elaborate method to prove it. Therefore these methods cannot be used in safety-critical systems, such as autonomous vehicles.

Although both groups of methods have their own advantages, all of them have pitfalls such as uncertain models in the case of classical solutions, or the large dataset, which is necessary for data-driven methods.

In the last decade, a new technique has been developed, which is called Model Free Control (MFC) Fliess and Join [2013]. This method does not require an accurate model of the system but an identification process is solved using the ultra-local model-based approach. This model is continuously updated during the operation of the control system, in this way, it can cope with highly nonlinear systems. This solution can also be fruitful for observer design. For instance Al Younes et al. [2015] proposes a Model Free observer design method for a quadrotor. However, there are some issues with the implementation of the ultra-local model-based control caused by the time-delays of the system. Therefore, a new formulation of the computation of the ultra-local model has been proposed in Hegedus et al. [2022], which is called the error-based ultra-local model.

The contribution of the paper is a novel observer design technique for autonomous vehicles. The proposed solution combines the error-based ultra-local model and LQ technique to provide high-performance level and robustness against changes in parameters. The effectiveness and operation of the proposed algorithm are illustrated through a vehicle-oriented estimation problem: lateral velocity.

The paper is structured as follows: Section 2 presents the error-based ultra-local model and gives a short introduction to LQ observer design, then details the combined design approach. In section 3, the vehicle-oriented example is presented including the main steps. The effectiveness of the proposed algorithm is demonstrated in the vehicle simulation software, CarSim in Section 4 Finally, the conclusion of the paper is summarized in Section 5.

2. OBSERVER DESIGN USING ULTRA-LOCAL MODEL

2.1 Error-based ultra-local model

The error-based ultra-local model was inspired by the original ultra-local model presented in Fliess and Join [2013]. The original ultra-local model is computed from the input signal (u) of the system, and ν^{th} derivative of the output (y). In the case of the error-based ultra-local model, two ultra-local models are considered. The first one is computed from the measured signals, and the second one is derived from a nominal model. The error-based model (Δ) is computed as an error of two models, as:

$$y^{(\nu)} = F + \alpha u \tag{1a}$$

$$y^{(\nu)}_{ref} = F_{nom} + \alpha u_{nom,ref} \tag{1b}$$

$$\underbrace{y^{(\nu)} - y^{(\nu)}_{ref}}_{e^{(\nu)}} = \underbrace{F - F_{nom}}_{\Delta_{\text{nom}}} + \underbrace{\alpha u - \alpha u_{nom,ref}}_{\alpha\tilde{u}} \tag{1c}$$

$$e^{(\nu)} = \Delta_{\text{nom}} + \alpha\tilde{u} \tag{1d}$$

The ultra-local models have one tuning parameter (α), which can be adjusted to the actual application purpose. When the error-based ultra-local model is used for controlling a system, an additional baseline controller is considered ($C(s)$) in order to eliminate the steady-state error.

$$\tilde{u}_{\text{MFC}} = \frac{-\Delta_{\text{nom},est} + C(s)e}{\alpha}, \tag{2}$$

However, in case of observer design, only the error-based ultra-local part is needed, which means $C(s) = 0$. More details on the error-based ultra-local model can be found in Hegedus et al. [2022].

2.2 Linear Quadratic Observer

Linear Quadratic Observer design is based on the state-space representation of the considered system, which can be written, in general form, as:

$$\dot{x} = Ax + Bu \tag{3a}$$

$$y = Cx \tag{3b}$$

where A, B, C are state matrices, x is the state-vector, y is the output of the system, u is the control input.

The goal of the observer design to minimize the error between the estimated states $\hat{x}$ and the real states x:

$$e = x - \hat{x}, \qquad |e| \to min! \tag{4}$$

The estimated state-vector $\hat{x}$ can be computed as:

$$\dot{\hat{x}} = A\hat{x} + Bu + L(C\hat{x} - y) \tag{5}$$

where L is the gain-vector, which contains the optimized gains for the observer

This gain-vector can be computed by minimizing the following cost function:

$$J = \frac{1}{2}\int_0^\infty (x^T Q x + u^T R u)dt \tag{6}$$

where x gives the state vector u is the control input and Q and R are weighting matrices.

3. VEHICLE-ORIENTED APPLICATION

In the followings, the proposed observer design is presented for a vehicle-oriented estimation problem, lateral velocity. The observer design consists of the following main steps:

(1) The determination of the nominal model.
(2) Selection of the required derivative order (ν).
(3) Computation of the nominal reference signals ($u_{nom,ref}$,y^{ν}_{ref})

(4) Tuning of the parameter α.
(5) Design of LQ observer based on the nominal model.
(6) Finally, the estimated states can be computed as: $\dot{\hat{x}} = A\hat{x} + B(u - \Delta) + L(y - \hat{y})$

The structure of the observer algorithm is illustrated in Figure 1.

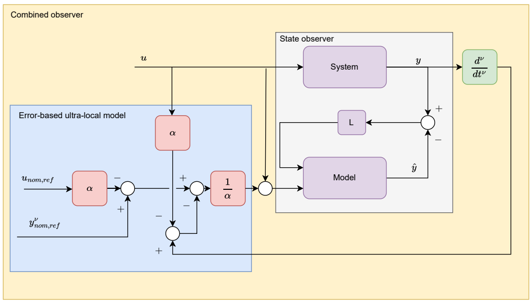


Fig. 1. The structure of the proposed observer

3.1 Determination of the nominal model

In this paper, the one-track bicycle model is used during the modeling phase of the lateral vehicle dynamics (Rajamani [2005]). The basic idea behind this model is that the front and rear wheels are replaced by one wheel each placed on the longitudinal axis of symmetry of the vehicle. The model consists of two main equations: lateral acceleration and yaw motion.

$$\ddot{\psi} I_z = C_f(\delta - \beta - \frac{\dot{\psi} l_f}{v_x}) l_f - C_r(-\beta + \frac{\dot{\psi} l_r}{v_x}) l_r, \tag{7a}$$

$$a_y m = C_f(\delta - \beta - \frac{\dot{\psi} l_f}{v_x}) + C_r(-\beta + \frac{\dot{\psi}}{v_x}), \tag{7b}$$

$$a_y = \ddot{y} + v_x \dot{\psi} \tag{7c}$$

where $\dot{\psi}$ denotes the yaw-rate and I_z is the yaw-inertia of the vehicle. Moreover, C_i gives the cornering stiffness of the tires of the front and rear axes and β is the side-slip angle. Moreover, l_i gives distance from the axes to CoG (center of gravity) and v_x is the actual longitudinal velocity. The lateral position of the vehicle is given by y and δ road wheel angle.

3.2 Selection of derivative order and computation of the reference signal

The goal of the observer design is to estimate the lateral velocity (v_y). Since the first derivative of the lateral velocity is the lateral acceleration, which is a directly measurable signal, ν is set to $\nu = 1$. Note that the measured lateral acceleration (a_y) has an additional component from the yaw-motion see: (7)(c), $\dot{v}_y$ is computed as $\dot{v}_y = a_y - v_x\dot{\psi}$. The reference signals ($u_{nom,ref}$,y^{ν}_{ref}) can be computed using a model predictive approach as detailed in Fenyes et al. [2022].

3.3 Tuning the parameter α

In the literature, there is no elaborate method to determine the optimal value of α. The determination of the tuning value is solved using an iterative algorithm. As pointed out by (Polack et al. [2019]), when $\alpha \to \infty$, the effect of the ultra-local model decreases and, in contrast, when $\alpha \to 0$, the ultra-local model becomes the major factor of the system. The computational process is based on a previously saved dataset, which contains the estimated ($\hat{v}_{y,i}$) and also the accurate value of the lateral velocity. The following optimization process can be formed, for determination of α with high performance-level:

$$\min_{\alpha} \sum_{i=1}^{n} (v_{y,i} - \hat{v}_{y,i})^2. \tag{8}$$

The main steps of the iterative algorithm are the following:

(1) Design a nominal observer using the nominal model.
(2) Set the value of α to a high value.
(3) Using the nominal observer and the actual value of α, evaluate the algorithm for a predefined test scenario
(4) Compute the value of the error between the reference value and the output of the system e_n, where n denotes the n^{th} iteration step.
(5) If $e_n \geq e_{n-1}$ or $n > N_{max}$, quit the iteration.
(6) Decrease the value of α then jump to Step 3.

3.4 LQ observer design

The goal of the observer design to minimize the error between the estimated and the measured lateral velocities:

$$e = v_y - \hat{v}_y, \qquad |e| \to min! \tag{9}$$

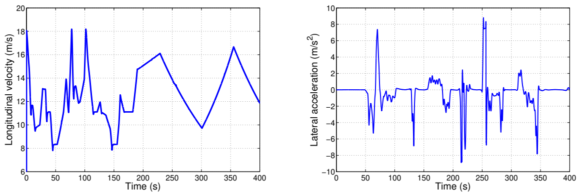
This performance can be guaranteed by appropriately chosen weighting matrices. In case of lateral velocity estimation, the matrices are chosen to $Q = diag(1000, 10)$, $R = 1$.

4. SIMULATION RESULTS

In this section, simulation result is presented to show the efficiency and the operation of the proposed observer design approach. The whole algorithm has been implemented in MATLAB/Simulink and CarSim environment. During the simulations, a B-class passenger car is used. Note that, the longitudinal velocity (v_x) is fixed to $v_x = 10m/s$ during the linear quadratic observer design.

In the first simulation, the vehicle is driven along the formula one track of Hungary. The track contains several sharp bends, where the lateral velocity can reach a high value. Furthermore, the longitudinal velocity of the vehicle varies as illustrated in Figure 2(a). The velocity profile consists of two main parts: the first one is the rapid changing part $t = \{0 - 200s\}$ and a slow changing part $t = \{200 - 400s\}$ in order to cover the whole operating range of the vehicle. Moreover, the measured signals ($a_y, \dot{\psi}$) are corrupted with white noises, whose variances: $\sigma^2_{a_y} = 0.04$ and $\sigma^2_{\dot{\psi}} = 0.01$.

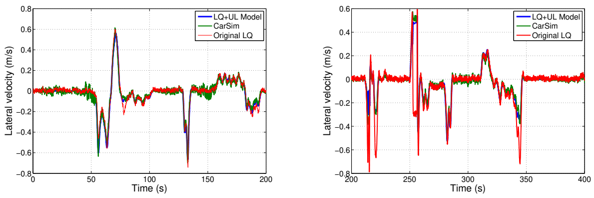
Figure 2(b) shows the lateral acceleration of the vehicle during the test scenario. It can be seen, that maximum of a_y is around $8m/s^2$, which is close to the physical limit of the vehicle.



(a) Longitudinal velocity (b) Lateral acceleration

Fig. 2. Longitudinal velocity of the vehicle

The estimated and the measured lateral velocities are depicted in Figures 3. Note that, this signal is shown without the applied sensor noises. In the first section of the simulation, both observers provide good results, however in the second half, the nominal LQ observer has a significant error. At that section, the longitudinal velocity exceeds the nominal value ($v_x = 10m/s$) for a long period of time, therefore the LQ observer cannot provide good results. However, it can be seen, when the velocity is close to the nominal value ($t = 300s$) the observer provides accurate results. In contrast, the combined observer algorithm estimate the lateral velocity in the whole simulation with low error. The last figure



(a) $t = 0 - 200s$ (b) $t = 200 - 400s$

Fig. 3. Estimated and measured lateral velocities

demonstrates the control inputs of the observer. The blue line illustrates the computed error-based ultra-local model (Δ) while the red line is the steering angle provided by the simulation software. In general, the ultra-local model has a higher amplitude, which aims to compensate for the unknown and unmodeled part of the system.

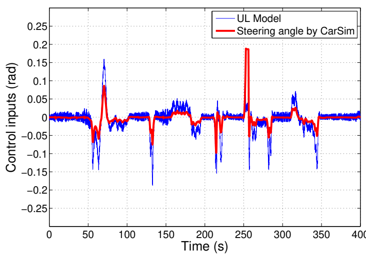


Fig. 4. Inputs of the observers

5. CONCLUSION

In this paper, a novel combined observer design method has been proposed using the linear quadratic and the ultra-local model approaches. The LQ observer was designed on a nominal model, which was not expected to be accurate. The ultra-local model-based part was able to approximate the unmodeled dynamics of the system and to eliminate its effect, which resulted in a more accurate estimation of the observed state. The proposed observer design algorithm has been implemented to a vehicle-oriented estimation problem: lateral velocity. The effectiveness and the operation of the presented algorithm have been demonstrated through an simulation example using CarSim.

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