2022-01-0626 Published 29 Mar 2022

Quantifying the Information Value of Sensors in Highly Non-Linear Dynamic Automotive Systems

Rhys Comissiong and Thomas Steffen Loughborough University

Citation: Comissiong, R. and Steffen, T., "Quantifying the Information Value of Sensors in Highly Non-Linear Dynamic Automotive Systems," SAE Technical Paper 2022-01-0626, 2022, doi:10.4271/2022-01-0626.

Received: 25 Jan 2022 Revised: 25 Jan 2022 Accepted: 06 Jan 2022

Abstract

In modern powertrains systems, sensors are critical elements for advanced control. The identification of sensing requirements for such highly nonlinear systems is technically challenging. To support the sensor selection process, this paper proposes a methodology to quantify the information gained from sensors used to control nonlinear dynamic systems using a dynamic probabilistic framework. This builds on previous work to design a Bayesian observer to deal with nonlinear systems. This was applied to a bimodal model of the SCR aftertreatment system. Despite correctly observing the bimodal distribution of the internal Ammonia-NOx Ratio (ANR) state, it could not distinguish which state is the true state. This causes issues for a control engineer who is less interested in how precise a measurement is and more interested in the location within control parameter space.

Information regarding the dynamics of the systems is required to resolve the bimodality. Therefore, a hierarchical dynamic Bayesian observer is proposed to observe the heteroscedastic nature of the uncertainty in ANR. This utilises the sampling-based Markov Chain Monte Carlo methods. The dynamic Bayesian observer successfully resolved the bimodality caused by the ambiguity in the NOx sensor by using transient information. The quality of the observation depends on the operating point, as it requires the transition point to be in the window to solve the bimodality. The knowledge of the history collapses the bimodal ANR distribution into a more certain unimodal distribution. This result can then be used for appropriate closed loop ANR control.

Introduction

Traditional methods for controller design are focused on minimising error between the plant and controller, to ensure robust performance given engineering trade-offs. For automotive applications these include torque and fuel efficiency, whilst meeting emissions standards. Due to system complexity, the time to design controllers and model plants has increased significantly. Typically, sensors and actuators are selected based on factors such as sampling rates, actuation rates, dynamic range, and cost. The quality of sensors are determined using metrics such as sensitivity to temperature, reliability, error detection and ageing. However, one of the major issues with sensor quality is that the confidence in the estimation is often unknown and not quantified.

Unlike the controller design there is no formal methodology for the selection of sensor and actuator configurations. Without a methodology, identification of an optimal control architecture is difficult. The difficulty of developing a suitable selection methodology is that real world automotive problems are nonlinear, which require non-gaussian nonlinear frameworks to resolve. The aim of this work is to determine the most suitable sensor configuration for a given system and control objective. Rather than spending a significant amount of time designing the entire closed loop control system, observation without closed loop effects is considered (Figure 1). This is particularly challenging when the system exhibits highly nonlinear behaviour, as is typical of the SCR near the NOx-Ammonia crossover limit. Within the framework of this work, the aim of this paper is to quantify the information gain by a sensor. Bayesian analysis is used to quantify the uncertainty within the system and enable the use of information-based metrics.

SCR is an aftertreatment system used for emission control located downstream of the Diesel Oxidation Catalyst (DOC) and Diesel Particle Filter (DPF) (Figure 2). The aim of the SCR is to convert nitrogen oxides (NOx) into diatomic nitrogen (N_2) and water (H_2O). The exhaust gas in the aftertreatment system is combined with a gaseous reductant, typically aqueous ammonia, or urea, which is then adsorbed onto a catalyst. Under steady state heavy-duty cycles, open-loop SCR control with fixed Ammonia (NH_3) to NO_x ratios can be used to achieve sufficient conversion of NO_x. Skaf et al [1] identified potential control variables including NH_3 conversion, NH_3 concentration, NO_x concentration and NO_x conversion. Each of these control variables have different control dynamics, disturbance dynamics and significance on the control of the knowledge of the system, thus it was essential to extend the nonlinear probabilistic framework to include the information analysis of dynamic systems. The dynamic nonlinear Bayesian observer proposed successfully resolves the bimodality caused by the ambiguity in the NOx sensor. It achieved this by using transient information and a differential operator to deal with the system dynamics. The quality of the observation depends on the operating point, as it requires the transition in the window to solve the bimodality.

When using information analysis for sensor selection, it is important to know both what information the sensor provides and when the sensor provides the information. There is a trade-off between control quality and system exploration to gain more knowledge of the state. Simply, the trade-off is between precision and confidence in the operating point for nonlinear systems. The results of this analysis could be applied to an aftertreatment SCR system by using the ANR states based on a few time steps back from the present. The results showed that there is more certainty about the state of ANR in the centre of the window, where the uncertainty width of the trajectory bundle is at its smallest. Through this uncertainty analysis, it was discovered that with a NOx sensor on the SCR output and information of the input disturbance to the SCR (engine output), there is sufficient knowledge to identify the internal state ANR and its associated uncertainty. This is useful as the ANR state cannot be directly measured on a heavy-duty SCR aftertreatment system.

The paper set out to answer the question of how much information could be obtained from a sensor and the RMSE plot (Figure 14) from the transient analysis achieved this. With the given SCR and NOx sensor model, it is not possible to extract more information regarding ANR from the system than this plot. To improve the process of information extraction, four methods were identified: Use different transients, increase length of estimator window, use multiple sensors, and develop a more realistic error model. This type of analysis can support systems design through the identification of sensing requirements based on information metrics.

Bibliography

1. Skaf, Z., Aliyev, T., Shead, L., and Steffen, T., "The State of the Art in Selective Catalytic Reduction Control," SAE Technical Paper 2014-01-1533, 2014, https://doi.org/10.4271/2014-01-1533
2. Comissiong, R., Steffen, T., and Shead, L., "Probabilistic Analysis of Bimodal State Distributions in SCAR Aftertreatment Systems," SAE Technical Paper 200-01-0355 (2020), doi:https://doi.org/10.4271/2020-01-0355.
3. Comissiong, R., Steffen, T., and Shead, L., "An Assessment of a Sensor Network Using Bayesian Analysis Demonstrated on an Inlet Manifold," SAE Technical Paper 2019-01-0121 (2019), doi:https://doi.org/10.4271/2019-01-0121.
4. Ravi, V., Jentz, R., Kumar, V., and Sharma, S., "Assessment of Exhaust Actuator Control at Low Ambient Temperature Conditions," SAE Technical Paper 2021-01-0681 (2021), doi:https://doi.org/10.4271/2021-01-0681.
5. Ali, I., Zhu, D., and Kumar, V., "Effects of Differential Pressure Measurements Characteristics on High Pressure-EGR Estimation Error in SI-Engine," *International Journal of Engine Research* (2021), doi:https://doi.org/10.1177/14680874211055580.
6. Zhu, D., Pritchard, E.S.R. et al., "Optimization of Rule-Based Energy Management Strategies for Hybrid Vehicles Using Dynamic Programming," *Combustion Engines* (2021), doi:https://doi.org/10.19206/CE-131967.
7. Dadam, S., Jentz, R., Ienzen, T., and Meissner, H., "Diagnostic Evaluation of Exhaust Gas Recirculation (EGR) System on Gasoline Electric Hybrid Vehicle," SAE Technical Paper 2020-01-0902 (2020), doi:https://doi.org/10.4271/2020-01-0902.
8. Willems, F., "Is Closed-Loop SCR Control Required to Meet Future Emission Targets?" SAE Technical Paper 2007-01-1574 (2007), doi:https://doi.org/10.4271/2007-01-1574.
9. Kwakernaak, H. and Sivan, R., *Linear Optimal Control Systems* (Wiley-Interscience, 1972)
10. Rabiner, L.R., "A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition," *Proceedings of the IEEE* 77, no. 2 (1989): 257-286, doi:https://doi.org/10.1109/5.18626.
11. Murphy, K.P., "Markov and Hidden Markov Models," in: , *Machine Learning: A Probabilistic Perspective*, (Cambridge: The MIT Press, 2012), 591-631.
12. Kang, H. and Farrell, P., "Experimental Investigation of Transient Emissions (HC and NOx) in a High Speed Direct Injection (HSDI) Diesel Engine," SAE Technical Paper 2005-01-3883 (2005), doi:https://doi.org/10.4271/2005-01-3883.
13. Salvatier, J., Wiecki, T.V., and Fonnesbeck, C., "Probabilistic Programming in Python Using PyMC3," *PeerJ Computer Science* 2 (2016): e55, doi:https://doi.org/10.7717/peerj-cs.55.
14. Simon, D., *Optimal State Estimation: Kalman, H and Nonlinear Approaches* (Hoboken, NJ: Wiley-Interscience, 2006)