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Title(English)	
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論 文 要 旨

THESIS SUMMARY

専攻： Department of	機械制御システム　　専攻	申請学位（専攻分野）： Academic Degree Requested	博士 Doctor of　（　工学　）
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要旨（英文 800 語程度）
Thesis Summary（approx.800 English Words ）

To solve the energy issue and the global environmental problem, automakers have developed high functional engines. Although engine control systems have been complicated, the development period is becoming shorter to meet market needs. It is difficult to develop products satisfying requirements in a short term through conventional development environments. For such a background a model based development (MBD), which is a development approach using virtual models and simulators, attracts much attentions as one solution to the problem.

To reduce CO2 emission, a control region for automotive engine system is pushed toward a boundary between normal and abnormal engine operations such as knocking and misfiring. The abnormal operation may damage engines seriously. Therefore a control method satisfying the boundary constraints robustly is highly demanded. To design such a controller through MBD, indeed, accurate numerical models of these boundaries are required. To identify the boundaries on an engine test bench, conventional methods need a lot of time and are costly. The goal of this research is to obtain accurate boundary models with an efficient input design algorithm.

In a field of automotive engine design, we usually consider static cases. This means that we obtain experimental data after an engine reaches steady states. The approach to determine input data is called design of experiment (DoE). The most common approaches to design the control region are a convex hull-based methods (e.g. Rapid Hull Determination Algorithm) and a way that minimizes the variance of the parameters (e.g. D-optimal design). However, since the static boundary models cannot deal with transient responses, they cannot be used directly for control system designs. In order to obtain accurate control models, it is necessary to use new identification methods of the dynamical system including the boundary detection signal.

In this paper, we develop a series of methods for the efficient engine system identification using statistical model such as Gaussian process (GP). Identification of the dynamical engine model can be divided into four phases: identification of static boundary model, acquisition of data using dynamical DoE, identification of dynamical model and online learning.

In the phase of the static boundary identification problem, we propose a DoE strategy based on the GP classifier with an expectation propagation algorithm. This method can describe accurate boundary models and provide an efficient input design algorithm using the generated model. This method can describe non-convex boundary and can determine the next measurement points near the boundaries. By this direct determination of additional inputs as points, the calibration time is expected to be much shorter.

In the phase of training data acquisition, we propose a new dynamical DoE method based on GP. This method is a model-based online algorithm that sequentially designs the next input by using GP models. Since the input design is performed while estimating dynamical boundary, it is not too conservative. In this algorithm, the input sequence design problem is formulated as an optimization problem that maximizes the sum of long-term prediction variances of the output with the static boundary constraint.

Then we propose a dynamic model structure based on a nonlinear auto-Regressive with exogenous inputs model as a control model of the automotive engine systems. This model is learned using a deep learning or a GP regression. Furthermore, we clarify relationships between the number of learning data, prediction / estimation accuracy and learning time by using numerical simulations. This approach is useful for deciding how to select a model learning method with respect to the number of training data. As a result, it is shown that when the number of learning data is small, the model based on GP is effective, and in the case where the number of learning data is large, the model using deep learning is suitable.

In the phase of online learning, we propose a robust recursive Gaussian process (RGP) as an effective online learning algorithm even when observed values are contaminated by outliers. GP model is suitable for identifying engine models that require modeling with a small amount of data. On the other hand, when online learning is performed using data-based approach such as GP and deep learning, outliers adversely affect model learning. In online learning of automotive engines, it is impossible to avoid the occurrence of outliers. Therefore a robust and fast online learning method is required. As a robust Kalman filter does, robust RGP explicitly estimates outliers by using l1 regularization to the RGP update optimization problem.

The validities of the proposed strategies are demonstrated by using an engine benchmark problem provided by the joint research committee of the Society of Automotive Engineers and Society of Instrument and Control Engineers, where the empirical combustion profiles with engine operating conditions and the knock model are implemented in this benchmark.