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題目(和文)	Koopmanアプローチを活用したモデル予測制御に関する研究
Title(English)	
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（博士課程）
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論 文 要 旨

THESIS SUMMARY

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学生氏名： Student's Name	金井　政樹	指導教員（主）： Academic Supervisor(main)	山北　昌毅　准教授
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要旨（英文 800 語程度）
Thesis Summary（approx.800 English Words ）

Model predictive control (MPC) is a versatile optimal control method that can determine the optimal input by explicitly considering the nonlinearities and constraints of the target system. In MPC, the accuracy of the prediction model has a significant impact on control performance. On the other hand, if a complex prediction model with nonlinearity is used, the computational cost of the optimization is increased at each control cycle. Therefore, the challenge is to improve prediction accuracy by taking nonlinearities into account while reducing the computational cost for real-time executions.

On the other hand, MPC methods utilizing lifting linearization based on Koopman's theory have been attracting attention in recent years. Lifting linearization is a method that lifts the state to a high-dimensional space using observation functions (observables), which are nonlinear outputs of the target system, and expresses the time evolution of the observables as linear dynamics. This allows us to obtain a high-dimensional linear model (lifted linear model) that expresses the nonlinear characteristics of the target system. By using this, it is possible to construct a linear model predictive control (LMPC) and is expected to significantly reduce the computational cost.

However, an accurate lifted linear model for a nonlinear system generally tends to have very large orders. This results in a relatively high computational cost, even for LMPC. On the other hand, when lifting linearization is performed in low dimensions using a limited number of observables, the prediction accuracy is generally deteriorated. For these reasons, even if utilizing the lifting linearization, there remains a challenge in achieving both improved prediction accuracy and reduced computational cost.

Therefore, the objective of this research is to propose MPC methods that combines high control performance based on accurate prediction with low computational cost by utilizing the Koopman approach.

The lifted linear model obtained based on Koopman theory is generally an approximate model of the nonlinear system. Therefore, regardless of the order of the model, prediction errors are inevitable. Therefore, this study takes the approach of constructing an LMPC with prediction error correction for a low order lifted linear model to achieve both high control performance based on accurate prediction and low computational cost.

First, we consider the case where the target system is known and propose an approximate lifting linearization that derives a lower order lifted linear model based on a known physical model. Then, we propose an LMPC that considers the approximate lifted linear model and the prediction error correction that takes advantages of the features of the lifting linearization. The proposed method introduces constraints that numerical relationships based on observables are satisfied between the elements in the lifted state at each step on the prediction horizon. Along with the additional constraints, we also introduce corrective inputs to ensure the feasibility of the optimization problem.

Then, to deal with the case where the target system is unknown, we propose an LMPC with prediction error correction using a prediction model identified in a data-driven manner. Here, we consider a nonlinear input affine system as the target system. It is known that for nonlinear affine systems, lifting bilinearization is more accurate than lifting linearization. For this reason, we present a method for identifying the lifted bilinear model by a data-driven manner, as well as a method for constructing an LMPC algorithm by linearizing the model at each prediction step and considering the prediction error correction method described above.

In addition, since a physical model of the target system is often available in industry, we will also consider how to apply the LMPC using the lifted bilinear model, considering the effective use of the known model. Here, we assume the situation where a nominal model with model error is obtained against the real plant. We then identify a model error model (MEM) that expresses the dynamics of the prediction error by the nominal model and consider using this model for prediction error correction. Since the model error model is generally a nonlinear system, lifting bilinearization is used to identify the MEM. The nominal

model and the identified lifted bilinear MEM are then integrated to form an error-compensated model, and an LMPC using that model is then proposed.
The prediction error correction method based on the observables used in the previous methods increases the number of constraints and optimization variables according to the number of observables and the length of the prediction horizon, which limits the effectiveness of the method. Therefore, finally, we further extend the LMPC using the lifting bilinear model described above and propose a scalable LMPC that does not require additional constraints or optimization variables, so that it can be applied to practical higher-order systems and conditions with long prediction horizons. The effectiveness of the proposed method is demonstrated using a quadrotor model as an example of a practical target system.