Abstract

This thesis considers the problem of stabilised control for a multirotor with an unknown suspended payload. The controller assumes no prior knowledge of the payload dynamics. The swinging payload negatively affects the multirotor flight dynamics by inducing oscillations in the system. An adaptive control architecture is proposed to damp these oscillations and produce stable flight with different unknown payloads. A data-driven system identification method forms part of the architecture and is demonstrated in simulation and with practical flight data. Model Predictive Control (MPC) is applied for swing damping control and is verified with Hardware-in-the-Loop (HITL) simulations.

A parameter estimator and Linear Quadratic Regulator (LQR) is used ~~in the~~ as a baseline architecture. The LQR uses a predetermined model of the payload, which is completed with estimates of the payload mass and cable length. The new architecture, proposed in this work, uses Dynamic Mode Decomposition with Control (DMDc) to estimate a linear state-space model and approximate the unknown dynamics. A short length of flight data is used for training. An MPC uses the data-driven model to control the multirotor and damp the payload oscillations.

A Simulink™ simulator was designed and verified with practical data. Within simulation~~s~~, both the baseline and proposed architectures produced near swing-free multirotor control with different payload masses and cable lengths. Even with a dynamic payload producing irregular oscillations, both methods resulted in stabilised control. Both architectures also showed effective disturbance rejection. Despite the baseline method using an accurate predetermined model, the proposed method produced equal performances without prior knowledge of the dynamics. The baseline performance degraded significantly for a different multirotor mass because this parameter was not considered as an unknown. In contrast, the proposed method consistently produced good performances.

The accuracy of the DMDc models was verified with practical flight data. The proposed control architecture was also demonstrated in HITL simulations. The hardware executed the MPC at the desired ~~speed~~ frequency, producing near swing-free control within a Gazebo simulator. Overall, it was shown that the proposed control architecture is practically feasible. Without knowledge of the payload dynamics, a data-driven model ~~is~~ can be used with MPC for effective swing damping control with a multirotor.

Uittreksel

Hierdie tesis hanteer die probleem van gestabiliseerde beheer vir ’n multirotor hommeltuig met ’n onbekende hangende loonvrag. Die beheerder aanvaar ~~veronderstel~~ geen voorafkennis van die loonvragdinamika nie. Die swaaiende loonvrag beïnvloed die multirotor-vlugdinamika negatief deur ossillasies in die stelsel te veroorsaak. ’n Aanpasbare beheerargitektuur word voorgestel om hierdie ossillasies te demp en ’n ~~’n~~ stabiele vlug met verskillende onbekende loonvragte te verskaf. âĂŹn Datagedrewe stelsel-identifikasiemetode vorm deel van die argitektuur en word in simulasie en met praktiese vlugdata gedemonstreer. Model Predictive Control (MPC) word toegepas vir swaaidempingsbeheer en word geverifieer met Hardware-in-the-Loop (HITL)-simulasies.

’n Parameter- afskatter ~~beramer~~ en Linear Quadratic Regulator (LQR) word in die basislynargitektuur gebruik. Die LQR gebruik ’n vooraf bepaalde model van die loonvrag, wat voltooi word met afskattings van die loonvragmassa en kabellengte. Die nuwe argitektuur, wat in hierdie werk voorgestel word, gebruik Dynamic Mode Decomposition with Control (DMDc) om ’n lineêre toestand-ruimte model te bereken ~~skat~~ en die onbekende dinamika te benader. ’n Kort lengte van vlugdata word vir opleiding gebruik. ’n MPC gebruik die data-gedrewe model om die multirotor te beheer en die loonvrag geossillasies te demp.

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A Simulink™ simulator was designed and verified with practical data. Within simulations, both the baseline and proposed architectures produced near swing-free multirotor control with different payload masses and cable lengths. Even with a dynamic payload producing irregular oscillations, both methods resulted in stabilised control. Both architectures also showed effective disturbance rejection. Despite the baseline method using an accurate predetermined model, the proposed method produced equal performances without prior knowledge of the dynamics. The baseline performance degraded significantly for a different multirotor mass because this parameter was not considered as an unknown. In contrast, the proposed method consistently produced good performances.

Die akkuraatheid van die DMDc modelle is geverifieer met praktiese vlugdata. Die voorgestelde beheerargitektuur is ook in HITL-simulasies gedemonstreer. Die hardeware het die MPC teen die verlangde frekwenste ~~spoed~~ uitgevoer, wat byna swaaivrye beheer in ’n Gazebo-simulator gelewer het. Oor die algemeen is dit gewys ~~aangetoon~~ dat die voorgestelde beheerargitektuur prakties uitvoerbaar is. Sonder kennis van die loonvragdinamika ~~word~~ kan ’n data-gedrewe model met MPC gebruik word vir effektiewe swaaidempingsbeheer met ’n multirotor.

Acknowledgements

Chapter 1

Introduction

1.1. Background

Recent years have seen a rise in the popularity of payload transportation with Unmanned Aerial Vehicles (UAVs) [11]. These payloads are usually categorised as either a sensor or freight [12]. Sensors like cameras or meteorological instruments can be carried by ~~a~~ UAVs for aerial photography or surveying. Payloads carried as freight include pesticides sprayed over agricultural land, medical parcels carried to remote areas or consumer deliveries.

Commercial package deliveries with UAVs have become especially popular. In 2015, the first Federal Aviation Administration (FFA) approved drone delivery was successfully completed by Flirtey in the United States [13]. Domino's pizza has also been delivered by Flirtey multirotors in New Zealand [14]. Another commercial example includes Wing food deliveries with multirotors in Australia [15].

Multirotor UAVs are commonly used for payload transportation tasks due to their hover and Vertical Takeoff and Landing (VTOL) abilities. In some applications, a payload is rigidly attached to the UAV. The flying characteristics of multirotors also allow them to transport suspended payloads, which is useful for arbitrarily shaped payloads or for delivering payloads without landing. In this configuration, the payload is suspended below the vehicle with a cable and the payload is free to swing during flight. This oscillatory motion affects the flight dynamics of the multirotor and makes stabilised control a challenging task.

Control becomes even more difficult with increased uncertainty of the payload dynamics. In some applications the payload dynamics are well known and constant, hence a controller can be designed based on an accurate predetermined model of the dynamics. However, package delivery applications often involve uncertainty of the payload parameters. Specific payloads such as elongated payloads or fluid containers add even more uncertainty to the system by inducing interesting dynamics which are also unknown before a flight. This significantly affects the flight dynamics of a multirotor and the controller may need to account for this uncertainty for effective control.

In summary, multirotor payload transportation is becoming increasingly popular. The suspended payload configuration offers strategic benefits but increases the difficulty of the control task. Furthermore, the uncertainty in payload dynamics makes the control task more challenging. In this study, a control architecture will be designed to address this problem.

1.2. Project definition and objectives

This project aims to design and implement a control architecture for stabilised control of a multirotor with an unknown suspended payload. The payload uncertainty should include parameter uncertainty and model uncertainty. Furthermore, the oscillatory motion of the payload significantly affects the multirotor dynamics. The proposed controller should be compared to previous work involving a swing damping controller for a suspended payload with an unknown mass and cable length.

In contrast to the architecture based on a predetermined model with only two unknown parameters, the proposed architecture should assume no prior knowledge of the suspended payload dynamics. A data-driven approach should be applied to estimate a dynamical model of the unknown dynamics. Based on the estimated model, a controller should stabilise the multirotor by actively damping the payload swing angles.

Therefore, the research objectives are stated as:

1. Investigate the literature regarding multirotor-payload controllers and specifically consider solutions for unknown suspended payload dynamics.
2. Derive a dynamical model to describe a multirotor with a suspended payload.
3. Identify and implement a baseline architecture with a system identification and control method for this system in simulation.
4. Design a data-driven system identification method for this system and implement it in simulation.
5. Design a controller based on the proposed system identification model and implement it in simulation.
6. Identify a hardware platform and software toolchain to implement the proposed control architecture.
7. Implement and verify the data-driven system identification method with experimental data from practical flights.

8. Implement, simulate and verify the controller algorithms on the practical hardware for effective swing damping control of the unknown suspended payload system.

1.3. Thesis outline

Chapter 1 provides the background of this research, the project definition and objectives, and the thesis outline.

Chapter 2 presents a study of the literature regarding multirotor payload transportation, with a focus on suspended payloads and uncertain payload dynamics.

Chapter 3 contains a derivation of a mathematical model for the multirotor and suspended payload dynamics, which is used for simulations and controller design.

Chapter 4 describes the baseline and the proposed system identification methods considered in this thesis. Furthermore, the performances of these methods are evaluated based on tests with simulation data.

Chapter 5 describes the different controllers and the corresponding controller design processes used in this project. Using the system identification models from the previous chapter, the controllers are also applied to the multirotor-payload system in simulation and the results are compared.

Chapter 6 provides an overview of the practical multirotor setup used for experimental work with the proposed algorithms. Thereby, the hardware components, software toolchain, and HITL simulations are discussed.

Chapter 7 presents and discusses the experimental results from implementing the system identification methods with practical flight data. HITL results are also presented to test the controller algorithms with the practical hardware and software systems.

Chapter 8 provides a summary of the work in this thesis. The major conclusions of this work are also presented and future recommendations are discussed.

Chapter 8

Conclusion

This thesis considered the design and practical implementation of a stabilising control architecture for a multirotor with an unknown suspended payload. A broad scope was considered which includes two different area of research, namely,

- Data-driven system identification of the unknown payload dynamics
- Optimal swing damping control of the multirotor-payload system

The content and outcome of this work will be discussed in this chapter.

8.1. Literature study

Existing solutions for stabilised multirotor control with a suspended payload were identified in the literature. The literature study showed that research seldomly includes experimental results or algorithm testing on practical hardware, even though this would provide valuable insight. It also showed that most studies do not account for uncertainty in the controlled system. A thorough study of the literature showed that some solutions account for parameter uncertainty, but very few assume no knowledge of the payload dynamics.

Furthermore, the few studies that achieved stabilised control despite unknown dynamics, counteracted the payload effect as an unknown disturbance instead of actively controlling the payload state. This places the focus on robustness rather than smooth control of the complete multirotor-payload system.

An LQR controller was identified as a popular baseline controller in the literature and was selected as the baseline swing damping controller for this work. The specific LQR implementation considered in this work is based on a previous study that only considers parameter uncertainty. This LQR controller is based on a linearised, predetermined model of the multirotor-payload system. The payload mass and cable length are unknown prior to a flight and are estimated with RLS and FFT estimators respectively.

8.2. System identification

The baseline parameter estimation technique was described and applied to data from SITL simulations with Gazebo. It was shown that the white-box model which uses the estimated parameters captured the general shape of the system state predictions well. The white-box model with parameter estimation technique was also applied to a dynamic payload simulation. An elongated payload was suspended from the multirotor and acted as a double pendulum, inducing irregular oscillations in the system. For this use case, the resultant white-box model predictions did not represent the general shape of the payload dynamics.

DMDc and HAVOKc were introduced as the data-driven system identification techniques proposed by this work. These linear regression techniques each produce a discrete, linear space-space model of the considered dynamics based on input and output data only. The conventional HAVOK is not designed to be applied to controlled systems. However, this algorithm was extended in this work to account for control inputs in a dynamical system and will be referred to as HAVOKc. The conventional DMDc algorithm was altered to include delay-coordinates in a similar way to HAVOK. Furthermore, the mathematical complexity of these techniques was described in detail.

These algorithms were applied to multiple SITL simulations for testing. Data was generated by tracking a sequence of random velocity step inputs with the standard PID controllers from PX4. This data was split into training and testing sets. The algorithms could then be trained on the set of training data and could be validated on the unseen testing set. The prediction accuracy of each model produced by these techniques was quantified with an NMAE error metric. ~~This metric is based on multiple model prediction runs from different initial conditions over a specified time horizon.~~

A hyperparameters search showed a Pareto elbow as a function of the number of delay-coordinates, q, such that increasing q passed this elbow does not significantly increase the model accuracy, but does increase model complexity. Furthermore, the ‘double-descent’ phenomenon was identified when testing with various lengths of training data. It was consistently observed in different experiments that increasing the length of training data past a specific point decreases the prediction accuracy. This is unintuitive, because longer lengths of training data are expected to increase model accuracy by reducing overfitting.

Both techniques were shown to be robust to measurement noise. It was also shown that the techniques consistently produced accurate models with a range of different system parameters. The techniques were also tested with the dynamic pendulum and the prediction models accurately captured the irregular oscillations, despite having no prior knowledge of the payload. This showed a major improvement compared to the white-box model. For the range of different tests the prediction accuracies of DMDc and HAVOKc models were similar, hence DMDc is preferred due to lower computational complexity.

8.3. Swing damping controllers

~~Furthermore, the~~ different controllers were discussed and tested. The cascaded PID controller was described and the gains of each control loop were tuned in simulation. This simulation environment was verified with practical data from the Honeybee multirotor and was shown to be an accurate representation of the actual system.

The baseline LQR controller was also described and the weights were tuned for the simulated multirotor-payload system. The LQR was designed based on the white-box model which uses estimated parameters for each different payload. The control architecture proposed in this work includes an MPC controller which uses a data-driven system identification model for predictive control. The MPC implementation from the Model Predictive Control Toolbox™ in Simulink™ was used and the algorithm was described in detail. This controller, using data-driven system identification models, was also successfully applied for swing damping control in simulation.

Numerous tests were performed to evaluate the combined system identification and control architectures. For each test, the system identification stages firstly produced the parameter estimates and identified model for the LQR and MPC approaches respectively. Thereafter, each controller was applied based on those results. For a payload with a single pendulum model, the LQR and MPC both achieved stabilised control resulting in near swing-free motion. The controllers showed similar swing damping performances, but the MPC produced a faster settling time. The control architectures consistently achieved swing damping control with different payload masses and cable lengths, despite parameter uncertainty for the LQR approach and no prior payload knowledge for the MPC approach. Both controllers also showed acceptable disturbance rejection during a constant unknown step input force to the multirotor.

The control approaches were also tested for the dynamic payload case. Despite the data-driven model showing a much better prediction accuracy than the white-box model, the LQR and MPC approached produced similar swing damping performances. It was shown that even though the data-driven model is accurate in the domain of the state and input vectors considered in training, the optimised trajectory of the MPC goes beyond that domain. Hence, the model approximation is inaccurate and the resulting MPC control is suboptimal. Both controller responses were not as smooth as for the single pendulum model. However, both controllers showed stabilised swing damping control of the system and reduced system oscillations quickly.

The controller architectures were also applied to a simulation where a different multirotor mass was used. The LQR controller induced undesirable, high-frequency oscillations in the system response due to the model inaccuracy. This is because the baseline approach only considers parameter uncertainty in the payload mass and cable length. However, the MPC approach produced the same swing-free motion shown in previous simulations and clearly outperformed the LQR approach. The proposed control architecture does not rely on prior knowledge of the system dynamics, therefore the architecture can adapt to unconsidered system changes without redesigning the implementation.

8.4. Practical implementation

For experimental work, the hardware and software toolchains were described. Numerous practical flights were performed with different payload masses, cable lengths, and with a dynamics payload. All conclusions made with simulation data for the system identification methods were verified with practical flight data. This further validated that the simulation environment is a good representative of the actual system. This ~~also~~ showed that DMDc produces accurate prediction models with practical levels of wind disturbances and measurement noise.

Finally, HITL simulations were performed to demonstrate the computationally intensive controller algorithm working with the actual hardware and software toolchain. This involved a complex system of different, interconnected software tools. The MPC algorithm ran as a standalone ROS node on the OBC and was generated from Simulink™ code. Tests showed that the OBC was acceptable for the processing requirements of the MPC and the algorithm could run at the desired speed. It was also shown that the final system produces smooth, swing damping control of the multirotor-payload system as seen in previous simulations.

Overall, it was shown that the full data-driven system identification with MPC control architecture produces swing damping control of the multirotor-payload system despite having no prior knowledge of the payload dynamics. It was demonstrated that this control architecture works for various configurations with different system parameters and even with a dynamic payload. Furthermore, it was demonstrated that an accurate data-driven prediction model could be determined from practical flight data with wind disturbances and measurement noise. It was also demonstrated that the available hardware fulfils the computational requirements of the proposed algorithms. Finally, it is concluded that the proposed control architecture is practically feasible for stabilised control of a multirotor and suspended payload with unknown dynamics.

8.5. Recommended future work

The current work can be continued to further show the practical feasibility of this approach. It can also be extended to improve the control performance or to solve different control problems with the same approach. Recommendations for future work include:

- Perform practical flights with the MPC to demonstrate the practical performance of the controller.
- Perform practical flights with a rigidly attached container with sloshing fluid to demonstrate the adaptability of this approach to unknown dynamics.
- Test the current solution using obstacle avoidance trajectories and manoeuvres that require the payload to follow a specific trajectory instead of a simple non-swing reference.
- Add a continuous excitation functionality to continue training the system identification model during flight and possibly adapt to time-variant uncertainty.
- Quantify the domain represented by the state and input vectors considered in the training data. This could be used to adjust the input signal during training to cover a larger domain and ultimately train a model that better represents the system dynamics. This would hopefully improve the controller performance with unknown dynamical models.
- Compare the proposed control architecture to a non-linear MPC using a non-linear data-driven model like SINDy