Staged Parameter Optimisation for a Robotic Bird Model

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ABSTRACT

This paper proposes a method to estimate a nonlinear mathematical model describing the dynamic behaviour of a robotic bird. Established knowledge on aircraft modelling and aerodynamics is used to derive an appropriate model structure. A new parameter optimisation method is developed, which consists of experiment design and staged parameter optimisation using datasets from test flights. The modelling method delivers promising results for predicting pitch and yaw of a model aeroplane and can be applied to the Robird when flight data become available.

Keywords

Robird, robotic bird, nonlinear model, staged parameter optimization, experiment design.

INTRODUCTION

Clear Flight Solutions has built the Robird Peregrine Falcon (Fig. 1), a remotely piloted robotic bird that uses flapping wings as a means of propulsion. The Robird has been successfully used to repel birds (e.g., at airports and farmland), in an environmentally friendly way [1]. It can fly with or without flapping its wings, which is referred to as *flapping* and *gliding* flight respectively.

Currently, the Robird can only be controlled manually by a few very experienced model aircraft pilots, which makes it unsuitable for broad application. The implementation of an autopilot could overcome this limitation. In order to design an autopilot, a mathematical model describing the dynamical behaviour of the Robird is needed.

Existing research contains two fields of interest. First, there is research focussed on modelling *real* birds that use wing deformation and vary feather configuration while flying [2], [3]. Since the Robird has rigid wings, these models cannot be used directly. Second, there exists research on insect-like flapping wing aircrafts [4], [5]. Scaling of insect-like models is impracticable and these models do not include the effect of gliding flight. Finally, model parameters cannot be estimated without disassembly and expensive lab experiments, such as wind tunnel tests. Since the Robird is already flying with multiple sensors[1], parameter identification using flight data is strongly preferred.

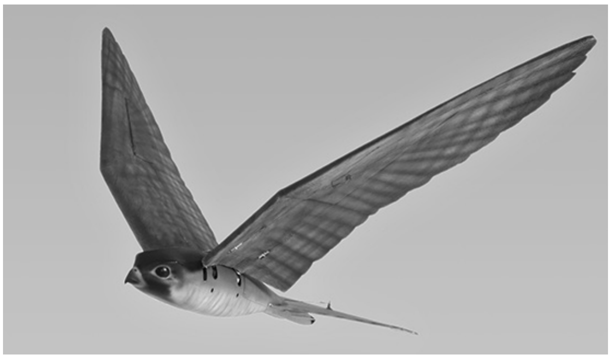

Figure 1: Robird Peregrine Falcon, source: [1]

This leads to the following research question: can we develop a method that automatically calibrates the model parameters of a nonlinear mathematical model, using flight data only? It is assumed that experimental data can be obtained through flights with the Robird. Moreover, it should be possible to perform various experiments with an increasing level of complexity, as described later.

At the time of this research, no Robird data were available. As a start, the method was executed on a model aeroplane[2]. It is assumed that the Robird its gliding flight is comparable to the behaviour of the model aeroplane, as both wings are fixed. The flapping flight cannot be studied with the model aeroplane and remains for future research.

METHOD

The method includes the derivation of the model structure, an initial parameter estimation and staged parameter optimisation combined with experiment design. The overall structure and the underlying reasoning are very general, enabling direct application to other aircraft.

Since this research is aimed at modelling the Robird, this section is still focussed on the Robird. The results section is based on adjusted equations of motion and initial parameter estimations for the model aeroplane.

Mathematical Model

A general model is given by

$$\dot{\xi}(t) = f\big(\xi(t), v(t), u(t)\big) \tag{1}$$

with states $\xi = \begin{bmatrix}\phi & \theta & \psi & \dot{\phi} & \dot{\theta} & \dot{\psi}\end{bmatrix}^T$,
airspeed data $v = \begin{bmatrix}\dot{x} & \dot{y} & \dot{z}\end{bmatrix}^T$ and
control input $u = \begin{bmatrix}\delta_{ailrs,left} & \delta_{ailrs,right} & \delta_{tail} & f_{flap}\end{bmatrix}^T$.

[1]ArduPilot 2.6 (3-axis accelerometers, 3-axis gyroscopes, altimeter) and 1 airspeed sensor (MPXV7002) in x direction.
[2]EasyStar RTF Electric Parkflyer (MPU13203)

The main goal is to model the dynamic behaviour of the Robird's orientation, which is described by pitch, roll and yaw (see Fig. 2). The Robird has four control inputs: tail deflection, two aileron angles and the flapping frequency.

The Robird has two modes, namely gliding and flapping flight. It is assumed that gliding flight is comparable to fixed-wing aircraft behaviour, as lift is generated by using current velocity and wing shape only. Therefore, fixed-wing aircraft models are used for modelling gliding flight. For flapping wing flight, a second model is made as aerodynamic properties change due to flapping. The model is based on the same equations as the gliding flight model, with an additional thrust term.

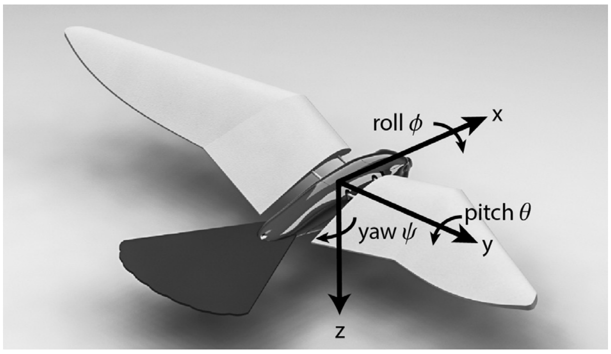

Figure 2: Model reference frame

Example: Gliding Flight Model

General model structures from [6], [7], [8] and [9] link aerodynamic forces and moments to translational and angular accelerations in 3 directions. Similar equations can be derived for the Robird, incorporating lift and drag corresponding to tail deflection δ_{tail} and aileron angles $\delta_{ailrs,left}$ and $\delta_{ailrs,right}$.

In gliding flight, the force and moment equations in x, y, z direction with angles ϕ, θ, ψ are [9]:

$$\begin{bmatrix} F_x \\ F_y \\ F_z \end{bmatrix} + mg_0 \begin{bmatrix} -\sin\theta \\ \cos\theta\sin\phi \\ \cos\theta\cos\phi \end{bmatrix} = m \begin{bmatrix} \ddot{x} + \dot{\theta}\dot{z} - \dot{\psi}\dot{y} \\ \ddot{y} + \dot{\psi}\dot{x} - \dot{\phi}\dot{z} \\ \ddot{z} + \dot{\phi}\dot{y} - \dot{\theta}\dot{x} \end{bmatrix} \tag{2}$$

$$\begin{bmatrix} M_x \\ M_y \\ M_z \end{bmatrix} = \begin{bmatrix} I_x\ddot{\phi} + (I_z - I_y)\dot{\theta}\dot{\psi} \\ I_y\ddot{\theta} + (I_x - I_z)\dot{\psi}\dot{\phi} \\ I_z\ddot{\psi} + (I_y - I_x)\dot{\phi}\dot{\theta} \end{bmatrix} \tag{3}$$

With mass m, moment of inertia I and gravitational acceleration g_0. F_x, F_y, F_z, M_x, M_y and M_z are aerodynamic forces and moments, caused by the wings, tail and ailerons.

The definition of all the parameters is given in Table 1. The lift forces L_i and drag forces D_i are described by [6]:

$$L_i = \frac{1}{2}\rho V_\infty^2 S_i \left[\frac{\partial C_{L_i}}{\partial \delta_i}\delta_i\right] \tag{4}$$

$$D_i = \frac{1}{2}\rho V_\infty^2 S_i \left[\frac{\partial^2 C_{D_i}}{\partial {\delta_i}^2}\delta_i^2\right] \tag{5}$$

with air density ρ, resulting velocity vector V_∞, surface S_i, derivative of lift and drag coefficients $\partial C_{L_i}/\partial\delta_i$ and $\partial^2 C_{D_i}/\partial{\delta_i}^2$, for $i = \{\text{wing}, \text{tail}, \text{ailerons}\}$.

The aerodynamic forces and moments are given by:

$$\begin{bmatrix} F_x \\ F_y \\ F_z \end{bmatrix} = \begin{bmatrix} L_{total}\sin\alpha - D_{total}\cos\alpha \\ 0 \\ -L_{total}\cos\alpha - D_{total}\sin\alpha \end{bmatrix} \tag{6}$$

$$\begin{bmatrix} M_x \\ M_y \\ M_z \end{bmatrix} = \begin{bmatrix} (L_{ailrs}\cos\alpha + D_{ailrs}\sin\alpha)t_k \\ (-L_{tail}\cos\alpha - D_{tail}\sin\alpha)h_t \\ (L_{ailrs}\sin\alpha - D_{ailrs}\cos\alpha)t_k \end{bmatrix} \tag{7}$$

with angle of attack α (the angle between V_∞ and the velocity in x direction) and the moment arms of the tail and ailerons h_t, t_k. L_{total} is the lift of the wings, tail and ailerons combined.

The equations require airspeed data $\dot{x}$, $\dot{y}$ and $\dot{z}$. However, the airspeed in y and z direction is not measured by the current sensors. Nevertheless, $\dot{z}$ can be estimated by differentiating the global height measured by the altimeter and transforming it to local coordinates, using rotation matrices [9]. Since there is no information about the airspeed $\dot{y}$, it is assumed that $\dot{y} = 0$.

Initial Parameter Estimation

The parameters (Table 1) can be categorised as:

- total mass and moments of inertia
- geometry, e.g. moment arms and areas
- coefficients of lift and drag

Moments of inertia about all axes are obtained from available SolidWorks models. Moment arms are estimated from the geometry of the Robird. Previous wind tunnel tests on the Robird [10] provide estimates of lift and drag coefficients of the wings. For parameters regarding ailerons and tail, lower and upper bounds are estimated. The precise values will be determined numerically.

Parameter Optimisation

Numerical optimisation is used to determine the remaining parameters. While flying, both control input u and sensor output η (consisting of roll, pitch and yaw) are recorded. Simulating the equations of motion with the same control input u results in an estimated output $\hat{\eta}$. The system is simulated using MATLAB's `ode45` function, which relies on the fourth-order Runge-Kutta numerical integration method.

The model performance is evaluated by comparing $\hat{\eta}$ with η, using the root mean squared error (RMSE). Since the outputs have different ranges, the error is normalised to enable comparison (NRMSE, Eq. (8)).

$$\text{NRMSE}_i = \frac{\sqrt{\frac{1}{N}\sum_{j=1}^{N}(\hat{\eta}_{i,j} - \eta_{i,j})^2}}{\eta_{i,max} - \eta_{i,min}} \tag{8}$$

with N data points, for $i = \phi, \theta, \psi$ (roll, pitch and yaw).

In parameter optimisation, the NRMSE is minimised. As the model is nonlinear in its parameters, the corresponding optimisation problem is also nonlinear and nonconvex. In order to reduce the risk of finding a local minimum, a global optimisation solver is used. MATLAB includes several algorithms, of which *pattern search* was selected for its robustness.

Pattern search is a direct-search method which dynamically adjusts the step size. Therefore, it is faster than a brute-force grid search. This is particularly useful when optimising multiple parameters at once.

Staged Parameter Optimisation

Despite using pattern search, optimising all parameter values simultaneously from arbitrary flight data will be very slow and may not yield a feasible solution at all. One solution is to split the full optimisation problem into smaller problems. In every subproblem, several parameter values are determined and then fixed.

The main idea behind staged parameter optimisation is to start with flight manoeuvres that can be described by a simple model. Because that model contains fewer parameters the optimisation will converge rapidly. Then in each stage the experiment becomes more advanced, requiring an extended model with additional parameters. The optimisation algorithm will only determine the additional parameters. Extra stages are introduced until the model capabilities are as desired.

Experiment Design

The staged optimisation requires careful experiment design, since parameters might be coupled. For the Robird, coupling takes place when rotating about multiple axes at the same time. For that reason, only tail deflection is used in the experiments of the first optimisation stage. Controlling the tail will only cause changes about the y axis (Fig. 2). Flight data is used to optimise all tail-related parameters. After convergence, the values are fixed.

In the second stage, only ailerons are used to control the Robird. This directly causes changes in roll and yaw, and due to coupling, also causes changes in pitch. Using the corresponding test flight data, all aileron-related parameters are determined.

The same procedure must be repeated for flapping flight. Optimisation is done for the same parameters, but will result in different values. For thrust, additional parameters should be introduced.

Validation

In order to validate the model, separate validation data are needed. In order to exploit the available data to the fullest extent, cross-validation is used [11]. Every flight test is performed 8 times. From the obtained datasets, 2 are selected for validation and the remaining 6 for parameter optimisation. This is done for all $C_2^8 = 28$ combinations. The NRMSE and Variance Accounted For (VAF) measure are calculated and averaged for all possible combinations [12].

The model is considered valid if $\mathrm{NRMSE} \leq 0.10$ and $\mathrm{VAF} \geq 80\%$. VAF is calculated according to Eq. (9).

$$\mathrm{VAF}_i = \left(1 - \frac{\mathrm{Var}(\eta_i - \hat{\eta}_i)}{\mathrm{Var}(\eta_i)}\right) \cdot 100\% \qquad (9)$$

for $i = \phi, \theta, \psi$ (roll, pitch and yaw).

RESULTS

The method was tested using a model aeroplane equipped with similar sensors as the Robird. The equations of motion and initial parameter estimates were adjusted accordingly. The experiment design for the staged parameter optimisation could still be applied, since the coupling effects are comparable. The optimised parameters, using cross-validation and data of 8 independent repetitions per stage, are stated in Table 1. The datasets typically contain 3 seconds of flight data (logged at 50 Hz). The validation results are listed in Table 2. An example of the pitch signal is plotted in Fig. 3.

Table 1: Determined parameters (model aeroplane)

p_i	**Description**	**Value**
$\frac{\partial C_{L_t}}{\partial \delta}$	Derivative of tail lift coef. w.r.t. δ	-0.0975 deg^{-1} (PO)
$\frac{\partial^2 C_{D_t}}{\partial \delta^2}$	Derivative of tail drag coef. w.r.t. δ	0.0117 deg^{-2} (PO)
$\frac{\partial C_{F_r}}{\partial k}$	Derivative of rudder force coef. w.r.t. angles k_L, k_R	-0.277 deg^{-1} (PO)
$C_{r,y}$	Coupling const. (roll vs yaw rate)	0.0078 (PO)
D_{roll}	Self damping term (roll)	-0.0019 J·s (PO)
D_{yaw}	Self damping term (yaw)	-0.0039 J·s (PO)
h_t	Moment arm tail	496 mm
t_k	Moment arm rudder	48 mm (PO)
S_w	Wing area	$22.2 \cdot 10^{-2}$ m^2
S_t	Tail area	$95.5 \cdot 10^{-4}$ m^2
S_r	Rudder area	$20.95 \cdot 10^{-4}$ m^2
I_x	Moment of inertia x-axis	$4.61 \cdot 10^{-3}$ kg·m^2
I_y	Moment of inertia y-axis	$5.85 \cdot 10^{-3}$ kg·m^2
I_z	Moment of inertia z-axis	$9.64 \cdot 10^{-3}$ kg·m^2
m	Mass	680.389 g
g_0	Gravitational acceleration	9.81 m/s^2

PO: found by Staged Parameter Optimisation

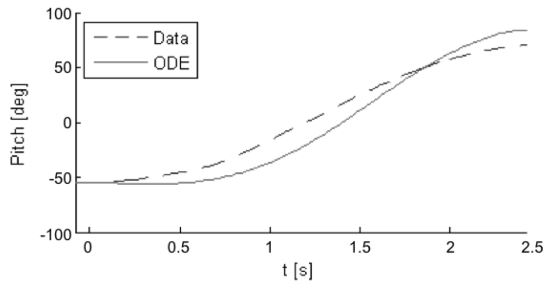

Figure 3: Measured and simulated pitch angle

Table 2: Error results from cross-validated data

	NRMSE	VAF
Roll	0.41	27.57%
Pitch	0.24	78.82%
Yaw	0.07	96.03%

DISCUSSION

Comparing validation criteria with the results in Table 2, it can be seen that the roll and pitch prediction requirements are not met as both NRMSE and VAF values violate the validation requirements. The yaw model, which is important for indicating the heading, is considered valid.

The suspected main reason for the problematic roll prediction is that the model does not account for the dihedral effect, see Fig. 4. Movement in y direction causes additional lift, leading to roll. As $\dot{y}$ cannot be measured with the current sensor configuration, this effect cannot be incorporated in the model. Adding an airspeed sensor in this direction is recommended for a better roll prediction.

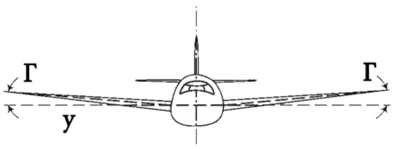

Figure 4: Dihedral angle Γ caused by movement y direction [13]

In general, better initial estimates and tighter bounds on the parameters will improve the numerical optimisation. For example, moments of inertia can be determined experimentally and aerodynamic behaviour of the ailerons and tail can be tested in a wind tunnel.

CONCLUSION

The yaw prediction gives sufficient outcome. The predicted pitch does not meet the requirements for NRMSE and VAF, but does show promising results. The experiment design and staged parameter optimisation can be used to estimate appropriate parameters of a model aeroplane model, using flight data only. The prediction requirements for roll and pitch are not met using the current sensor configuration. It is expected that adding an airspeed sensor in y direction will improve the result.

The proposed method is able to automatically calibrate unknown parameters for yaw prediction of the model aeroplane. It also shows potential in predicting the pitch angle. Validating the modelling method for the Robird remains for further research, in particular for flapping flight. The method can be applied to the Robird as soon as flight data become available.

ROLE OF THE STUDENTS

This research is carried out by four students of the department of Mechanical Engineering of Delft University of Technology. The project was run in collaboration with Nico Nijenhuis (Clear Flight Solutions) and supervised by Prof. Dr. Robert Babuska. Clear Flight Solutions proposed the topic: creating a dynamic model. During the project, Marjolijn and Jan were responsible for determining the model structure. Marjolijn initialised the parameters and Sander was responsible for the parameter estimation. He defined the used algorithm, implemented the equations of motion and validated the model structure. Jan came up with the specific test routines that were needed for the staged parameter optimisation. Bart identified the available sensors and took care of processing the data.

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