System identification of a remotely-operated flight vehicle

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This paper discusses the system identification of a typical remotely-operated flight vehicle (ROFV) known as Subzero III. The process characteristics of Subzero III are analysed qualitatively based on its first-principle model in Matlab/Simulink. This analysis provides the basis of why linear single-input/single output (SISO) system identification can be used for modelling the vehicle dynamics. Excitation signal design for system identification is discussed in detail. System identification simulations with the first-principle model in Matlab/Simulink are presented, followed by system identification tests in an experimental tank. Finally, the models obtained through the simulation and experimental study are compared and analysed.

INTRODUCTION

Subzero III is a torpedo-shaped underwater flight vehicle that has been built by the Institute of Sound and Vibration Research (ISVR), University of Southampton. The vehicle is 1m long with a diameter of 10cm. The payload carried is a maximum of 3kg with a target speed of 0-8kt (approximately 0-4m/s) and a depth capability of 6m. The duration of a mission was designed to last 15min. The vehicle is shown in Fig 1. In Subzero III, the thruster system consists of a propeller, which is linked to a DC motor and gearbox by a steel shaft with a universal coupling. The DC motor is controlled by a pulse width modulated (PWM) drive running at 800Hz. On the tail are mounted the four control surfaces: two rudders and two sternplanes. The two rudder surfaces are linked together to form a single rudder, and the two sternplane surfaces are linked together to form a single sternplane.

AUTHORS’ BIOGRAPHIES

Meihong Wang received his PhD in electronics and electrical engineering from University College London in 2002. After that, he was a postdoctoral research associate at Imperial College London. He later became a postdoctoral research fellow at the University of Plymouth. His research interests are system identification, process monitoring and model predictive control. Since writing this paper, Dr Wang has taken up employment as a senior control engineer with Industrial Control Group, Alstom Power Technology Centre, Whetstone, Leicester, UK.

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The rudder has an input range from -20deg to +20deg and the sternplane has an input range from -30deg to +30deg.

Feng and Allen have presented the development and validation of a dynamic model of Subzero III. The model is based on six degree-of-freedom (DOF) non-linear motion equations and includes the dynamics of the actuators. The non-linear model of Subzero III has been implemented with Matlab/Simulink (The Mathworks; Natick, MA).

The novel contribution of this paper is the use of system identification to find the dynamic model of a typical remotely-operated flight vehicle (ROFV). Rules for excitation signal design in system identification are given in detail. Special measures have been taken to avoid numerical issues in the identification of such a system where integral action is present. System identification simulation with the Matlab/Simulink model of Subzero III and full-scale tank experiments are used to support the study.

QUALITATIVE ANALYSIS OF THE SUBZERO III

To gain a priori knowledge for system identification, the process is qualitatively analysed based on the first-principle Matlab/Simulink model of Subzero III. This model has been validated by tank tests. Therefore, it can be viewed as an accurate representation of Subzero III.
Interaction between different channels
In the Matlab/Simulink model of Subzero III, the motor command input is used to control the duty cycle of the DC motor. The motor command has an input range from 0 to 2100 (no unit needs to be specified). Fig 2 shows the step response when the rudder is used as an input under the condition that the motor command input is 522 and the steady-state achieved. From Fig 2, the forward speed is nearly constant at 1.3 m/s, and the cross-coupling between different channels can be observed to be very weak. That is to say, when rudder is used as an input, the main (or dominant) output is yaw, with weak cross-coupling between rudder and forward speed, rudder and depth.

Fig 2: System responses when a step input is applied in the rudder and the motor command is fixed at 522

Fig 3: System responses when a step input is applied in the sternplane and the motor command is fixed at 522

Fig 3 shows the step response when the sternplane is used as an input under the condition that the motor command input is 522 and the steady-state achieved. From Fig 3, it will be seen that when the sternplane is used as an input, the main (or dominant) output is depth, but there is also a weak cross-coupling between sternplane and forward speed.

Linearity
Linear systems are those systems whose input-output relationship possesses the property of superposition. If a system has an input $x(t)$, then its output is $y(t)$. When its input is $x(t)$, then its output becomes $y(t)$. The superposition principle states that when the system has input $ax_1(t)+bx_2(t)$, its output must be $ay_1(t)+by_2(t)$ in which $a$ and $b$ could be any constants.

Fig 4 was generated to further analyse whether the sternplane-depth channel is linear or non-linear. In Fig 4, different step responses are shown when the sternplane is used as an input under the condition that the motor command input is fixed at 522 and that the steady-state has been achieved. In the left top panel, the sternplane step input with a 2deg (deg representing angular degree) amplitude was applied from 15s to 40s. The right top panel shows its response. In the same way, the two panels in the second row show the sternplane step input with a 3.5deg amplitude and its corresponding step response. In the two panels of the third row, sternplane step input with a 5.5deg amplitude was compared with the sum of the step responses in the first and second rows. It indicates a close fit (solid line vs dotted line in Fig 4). The two panels in the bottom rows show the sternplane step input with a 9deg amplitude. This step response is also compared with the sum of the step responses in the second and third rows. The minor difference between the two lines (solid line vs dotted line) indicates the minor non-linearity.

From Fig 4, the sternplane-depth channel still can be viewed as a linear system even though there exists minor non-linearity. The rudder-heading angle channel can also be analysed in a similar way and similar conclusions derived.
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Conclusion on the analysis of the Subzero III process
The analysis in this section provides the basis of why a linear single-input/single-output (SISO) system identification method that is explored in the following sections can be used to model the vehicle dynamics. It should be clarified that this conclusion is effective only when the motor command is fixed which results in a nearly constant forward speed. One might find that the dynamics are not linear when variable motor commands are applied in one test. It should also be noted that the input range used in the analysis is from -10deg to +10deg while the input limits are much larger (+20deg for rudder and ±30deg for sternplane). The reason for doing so is that the model identified is for control, and the control action is generally much smaller than the input limits.

SYSTEM IDENTIFICATION
Generally, there are two ways to obtain a dynamic model for a specific system. One way is modelling according to its physical laws. Feng and Allen presented the development and validation of the dynamic model of Subzero III according to physical laws (here the physical law is a six-degree-of-freedom non-linear motion equation). The other method is system identification. System identification deals with building mathematical models of the dynamic systems based on the observed data.

The motivation for system identification
In Feng and Allen’s some hydrodynamic derivatives are gained from tank tests, while the other coefficients are estimated from the Ocean Voyager (an autonomous underwater vehicle (AUV) which is geometrically similar to Subzero III) developed by Florida Atlantic University which kindly made available the model data.

Conventional hydrodynamic derivative identification methods involve towing tank trials of a vehicle itself or of a scaled model of the vehicle. The error in the estimate of some of the parameters can be as much as 50%. These kinds of tests allow for a complete model, but are lengthy, complex and expensive. As a consequence, system identification of a simplified model is to be preferred for vehicles as it can be simply and cheaply repeated when a significant variation in the system structure occurs.

Important concepts in system identification
In system identification, there are four basic procedures: the experiment design (such as excitation signal design and sampling rate selection); the model structure selection; the parameter estimation method; and the model validation. To guarantee the input-output data contains the system dynamic information, the excitation signal must be persistently exciting (PE) which means that the excitation signal must excite all the possible modes of the dynamic system. Model validation is also at the heart of the identification problem. It determines whether the estimated model can be accepted. System identification theory is fairly mature in general. Here, only these two important concepts will be discussed in detail since they will be repeatedly used in the simulations and experiments.

The excitation signal design
The commonly used perturbation signal in linear system identification is the pseudo-random binary sequence (PRBS) signal. It has a flat power spectrum and an impulse for the autocorrelation function like white noise. PRBS is used in the identification of this vehicle. The PRBS signal should cover the frequency band of the identified system so that it satisfies the PE condition of system identification. For better estimation accuracy, the frequency band of the PRBS signal must be carefully designed in different cases.

The Nyquist frequency is the bandwidth of a sampled signal, and is equal to half the sampling frequency of that signal. If the sampled signal represents a continuous spectral range starting at 0Hz (which is the most common case), the Nyquist frequency is the highest frequency that the sampled signal can unambiguously represent. Assuming the sampling rate is $T_s$, then the Nyquist frequency is $\frac{\pi}{T_s}$ in rad/sec (or $\frac{1}{2T_s}$ in Hz).

If the PRBS signal bandwidth required is $f_b$, then the real frequency range that the PRBS covers is:

$$f_b = \frac{\pi}{T_s}$$

This value should be $k$ (typically, two to three) times the system bandwidth:

$$\omega_b = \frac{1}{\tau}$$
(assuming that the dominant time constant \( \tau \) in a first-order plus dead-time [FOPDT] model). Therefore,

\[
f_b = \frac{z}{T_c} = k + \frac{1}{\tau}
\]  

(1)

In another form,

\[
f_b = k + \frac{T_c}{\tau} + \frac{1}{\pi}
\]  

(2)

The dominant time constant \( \tau \) can be determined in different ways. The simplest way is to apply a step into the system and then analyse the step response. The dominant time constant \( \tau \) can be determined by evaluating the time the system requires to vary 63.2% of the total variation (this analysis assumes the system model is first-order plus dead-time (FOPDT)). Another way is to plot the Bode diagram and then find the frequency

\[
\frac{1}{\tau}
\]

at which its amplitude is 70.7% of the maximum amplitude, or 3dB less than the maximum magnitude expressed in dB.

**Model validation**

Model validation is to determine whether the identified model can be accepted. Model validation is done through the analysis of the residuals (or the prediction error). The principle for passing model validation is that the residuals should be white and independent of the input.\(^3\)\(^4\) That is

\[
r_{E(t)} = E[e(t + \tau)e(t)] = \delta(\tau)
\]

(3)

\[
r_{uu(t)} = E[e(t + \tau)u(t)] = 0
\]

(4)

in which \( \delta(t) \) is the prediction error and \( u(t) \) is the input.

The system identification toolbox provides a function resid for this purpose. With resid, the auto-correlation function of the residuals and the cross-correlation between the residual and the input are computed and displayed. The 99\% confidence intervals for these values are also computed and displayed as dotted curves. The computation of these values is done assuming the residuals to be white and independent of the input. Therefore, the test results should not be beyond the 99\% confidence intervals.

**SIMULATION**

To provide guidelines for the system identification tank experiments, system identification simulations with the first-principle model\(^2\) in Matlab/Simulink were first undertaken. In the interests of brevity, only the rudder-heading angle channel is reported here.

Rudder-heading angle channel

As discussed in the section dealing with the qualitative analysis of Subzero III, the rudder-heading angle channel is an integration process which is a disadvantage for system identification. Therefore, a derivative block is added immediately after the process (ie, before the output). The time trends of the open loop system identification for rudder-heading angle channel are shown in Fig 5.

As can be observed from the left top panel of Fig 5, the motor command was fixed at 522 so that the forward speed is at about 1.3m/s. Based on equation (2), the frequency band from 0 to 0.3 was designed for the PRBS signal because the system without the integration block has a dominant time constant around 0.3s. From the middle left panel in Fig 5, the excitation used is a PRBS signal with frequency band from 0 to 0.3 and the amplitude is 8deg. The sampling time used is 0.125s. The number of sampled data used for identification in the simulation is 400.

The Box-Jenkins (BJ) model is used with the prediction error method (PEM) for parametric estimation. This is implemented with the function bj in the system identification toolbox. Given this model structure, the model order then has to
be determined. One may choose high-order models for both the plant and the noise, but this may violate the parsimony principle. The practice used to determine the model order here is to find the lowest order that can pass model validation. The principle for model validation is that the residual should be white and should also be independent of the input. The practical experience is that it could mean large errors in parametric estimates when either auto-correlation or cross-correlation is beyond the 99% confidence intervals in model validation.

The Bode plot, Nyquist plot and step response plot of the obtained model are presented in Fig 6. One characteristic of the process is its strong integration action which is observed from the left top and right bottom panels of Fig 6.

EXPERIMENTATION

Experiments were performed in the Lamont tank located at the University of Southampton. The Lamont tank is approximately 30m in length, 2.5m in width and 1.20m in depth.

Rudder-heading angle channel

During this experiment, the excitation signal injected into the rudder input was still PRBS. The frequency band of the PRBS signal is from 0 to 0.3 with the sampling time 0.125s. That is to say the Nyquist frequency of the excitation signal was $2.4\pi$ rad/s. The amplitude of the PRBS signal is from -8deg to +8deg. No excitation is injected at the first 20 samples because the ROFV had to speed up from a static condition to its working stage. Caution should be taken in the length of the PRBS signal generated. If the length of the PRBS signal generated is much larger than the length of the PRBS signal applied in the system identification experiment, then the actual excitation signal spectrum could be quite different, as expected.

As previously observed, the channel exhibits strong integral action. In order to avoid the numerical issue for system identification, the output data heading angle was first filtered by a derivative block. In this way, an integration block has to be added in the transfer function obtained from the identification. Otherwise, if no measure is taken and the data collected is directly used for system identification, the frequency response at low frequency ranges could be unacceptable. Fig 8 shows the experimental measurements compared with the corresponding one-step ahead prediction from the identified motor, so no unit needs to be specified) which leads to the forward speed of nearly 1.3m/s. The number 100 is different from 522 because different scaling parameters were used in the Simulink model and the ROFV respectively. During the experiment, there was no control action for the sternplane. The number of the sampled data used for identification in the experiment is 120. This number is restricted by the length of the Lamont tank.
model. The match was not perfect, but is acceptable. This relatively-poor match may be caused by the dead band in rudders and/or the two rudders being not well-aligned (since the two rudder surfaces are linked together so that they can be viewed as a single rudder).

The obtained model expressed in transfer function form is

\[
\frac{Y(s)}{R(s)} = \frac{0.2373s^2 + 0.4734s - 21.73}{s^2 + 2.793s^2 + 41.7s}
\]  

The Bode plot, Nyquist plot and step response are shown in Fig 9. The insight from the experiment process is that the experiment results can be improved in the following two aspects:

1. The ROFV itself has to be improved. Currently, the actuator (the rudder here) exhibits obvious dead band. This could explain why the identification results from simulations are richer in dynamics, while the identification results from experiment are of lower order.

2. A tank that is longer, wider and deeper than the Lamont tank currently used can give the ROFV more manoeuvrability space in experiments. This will be helpful for the identification of the ROFV dynamics since the samples used for identification could be larger and the amplitude of the excitation signal could also be larger.

RESULT DISCUSSIONS

This section compares the identification results from the previous sections dealing with simulation and experimentation, respectively.

Rudder-heading angle channel

From Fig 10, it will be seen that the identification results from simulation and experiment are consistent with each other. This can be observed from the fact that the solid line and the dotted line have the same shape in all the four panels of Fig 10. The difference in gain can be seen from the left top and bottom right panels. From the left bottom panel, slight difference in phase exists for high frequencies.

The differences between results obtained from simulation and experiment may be due to the following factors:

1. Some hydrodynamic derivatives in the Matlab\Simulink model are gained from tank tests and the other coefficients are estimated from the Ocean Voyager developed by Florida Atlantic University. This makes the Matlab\Simulink model an approximation of the real ROFV.

2. The forward speeds in simulation and in experiment are slightly different (1.27 m/s v 1.22 m/s) as can be observed from Figs 5 and 7.

3. The actuator (the rudder here) exhibits obvious dead band.

CONCLUSIONS

In this paper, open loop system identification has been employed for the rudder-heading angle channel of a ROFV. A pseudo-random binary sequence (PRBS) signal is used to excite the system. The excitation signal design has been discussed in detail. A Box-Jenkins model structure is then combined with a prediction error method for parametric estimation. Special measures have been taken to avoid numerical issues in the identification of such a system with integral action being present. The identification results from simulation and experiment are consistent with each other.

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