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MEASUREMENT ERRORS DETERMINATION USING IDENTIFICATION TECHNIQUES

Abstract. Identification of measurement errors applied to UAV Cularis flight-test data is presented. Data preparation for identification process is considered as it often decides of the successful identification. The problem of data synchronization is solved on the signal processing level by introducing interpolation procedure before applying identification algorithm. The identification method based on quazi-linearization optimization technique together with relaxation strategy is implemented in Matlab environment in order to pursue simulation tests. The nonlinear airplane equations of motion are formulated in body –axis and only kinematic quantities are exploited. The preliminary simulation test results indicates successful identification of measurement errors.

Keywords: system identification, flight data processing, UAV modelling.

1. INTRODUCTION

CAN bus advantages: cost effectives and efficiency as well as capability for system to share data across a common media caused that it is commonly used in avionic systems. It is used as major or redundant network. It enables in-flight data integration and analysis as well as off-line analysis using data from data logger, where data from CAN bus are stored. As flight test are expensive, the data processed in details after the flight, enables to extend capabilities of aeronautical systems and increase the safety of the flight.

In aeronautics, data gathered form the CAN bus may be used in off-line identification process. A system identification may be defined as a process of constructing an adequate mathematical model of a system based on data gathered during an identification experiment. For practical applications combination of a dedicated model and a proper identification method generates the useful simulation model. Such model with identified parameters may be exploited to investigate performance of flying vehicles such as: airplanes, rotorcraft and their embedded systems in design and development processes. Identified models are exploited in various fields for military and civil applications especially in design and control of dynamic systems as airplanes [7, 18, 22, 23], rotorcraft [2, 24], ships and submarines [1, 15], aeronautical and aerospace systems [19, 20, 21], mobile robots [25], rail-vehicles [12, 13] and others [16].

The identification focuses on adjusting the model parameters to mimic all important features of the considered existing system, it exploits data gathered during system operation (CAN bus in case of airplane) by various sensors. The quality of this data is crucial and implies on accuracy of identified model. In that case data preparation for identification is a key issue, which in many cases decide of the successful identification but is currently neglected, while the focus is placed on the identification algorithm. Also the identification process concerns mostly estimation of model of an object parameters. In the paper identification procedure is exploited in order to determine measurement error in data gathered form the sensors. The practical problem of dealing with unsynchronized data form the measurements is solved using an interpolation procedure.

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2. FLIGHT TEST DATA ANALYSIS

UAV identification of measurement error concerns data corresponding to variables important for further airplane identification. These variables usually are:

- control surface deflection (primary- elevator, ailerons, rudder; other-flaps, speed brakes, spoilers),
- linear accelerations in 3 axes,
- angular rates in 3 axes,
- angular accelerations, which may -it significantly increases accuracy of estimation,
- attitude angles,
- air data: angle-of-attack, angle-of-sideslip-mechanical vanes, airspeed-Pitot tube or propeller,
- static pressure,
- engine parameters.

Ideally the sampling rate of all data should be the same and data channels should be synchronized. Raw data from INS are the most wanted or at least cut-off frequency of the filter included must be high enough. Anti-aliasing filter should have the same cut-off frequency in case of all measurements (then signals will have the same time delay introduced by this filters). The signal-to-noise ratio value should be near 10:1.

In the paper data of the Unmanned Aerial Vehicle named Cularis gathered during flight test dedicated to identification of airplane model parameters are exploit [9, 17]. The manoeuvres performed during the tests are following: short period motion maneuver**,** phugoid motion maneuver**,** push over-pull up maneuvers, level-turn**,** thrust vibrations, bank-to-bank roll, Dutch roll maneuver, steady heading steady sideslip (SHSS) maneuver, acceleration-deceleration maneuvers.

The data from all maneuvers, as well as data recorded between these maneuvers, are used for identification of measurement errors. The statistical analysis of data, indicate the problem with data synchronization. The problem is connected with different frequencies used by sensors. But even taking into account that problem, the differences in sampling interval concerns all the variables described by gathered observations.

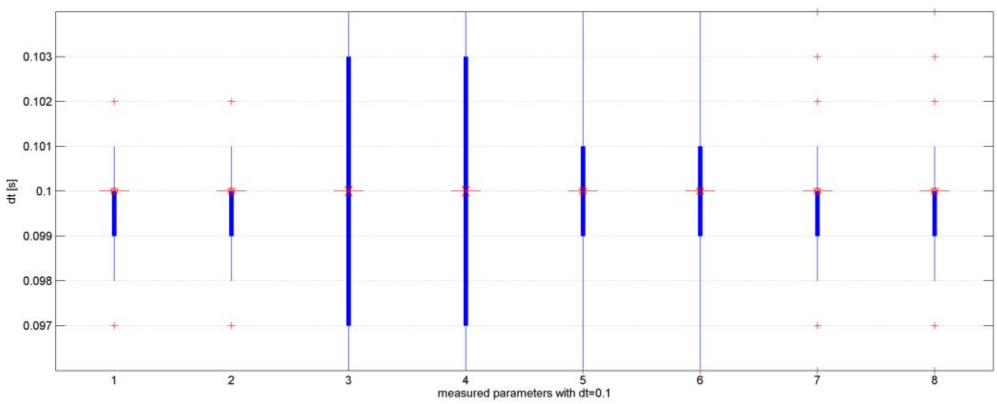

Fig.1. Boxplot representing each variable measured during flight tests with sampling interval *dt=0.1* [s]

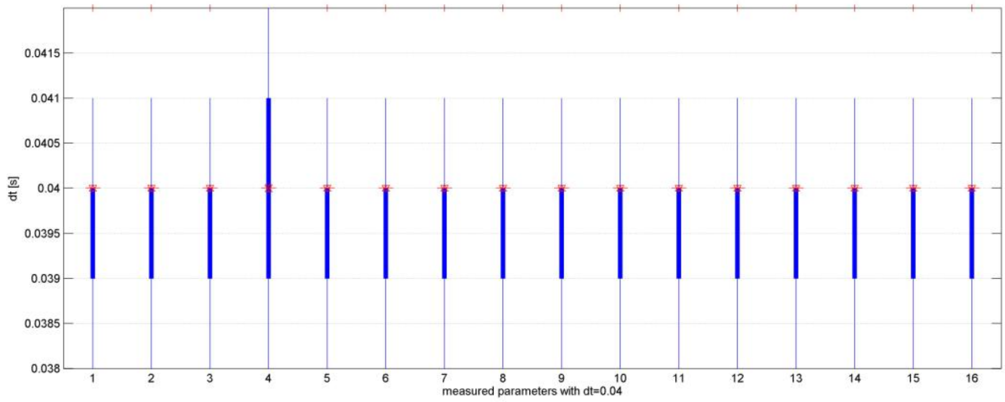

Fig.2. Boxplot representing each variable measured during flight tests with sampling interval *dt=0.04* [s]

There are two frequencies of data logging, which may be seen in sampling intervals. Variables measured with the sampling interval *dt=0.1* [s] (that results from the sensor frequency) are gathered on the same diagram (Fig. 1). While in the Fig. 2., variables logged with sampling interval *dt=0.04* are presented. In both cases median is placed almost in the sampling interval. There are two parameters which has the first and third quartiles of value significantly further form the reference one (*dt=0.1* [s]). In the second case, the boxplots of all variables but one are almost identical. There may be seen a tendency to sampling intervals of lower value than 0.04. When the range of variables is analyzed, it may be observe that in case of the sampling interval *dt=0.1* [s], there appear significantly higher spread of sampling interval values than in the other case. Even slightly unsynchronized data in case of identification process may cause major differences in identified model and real object behavior. Even very efficient and proved to enable successful identification method will not bring accurate solutions, when gathered data are not previously well-preprocessed and prepared.

3. INTERPOLATION TECHNIQUE

Data gathered during flight test are processed using Matlab environment. The problem of data synchronization is solved on the signal processing level by introducing interpolation procedure before applying identification algorithm. In the study the piecewise cubic Hermite interpolating polynomial is applied [14]. Taking into account the purpose of further data exploitation in identification process, the advantage of these interpolation method is not overshooting breakpoints, as they brings important information strictly form the sensors and the interpolation should only smoothly enable to generate additional sample data between the measured points. In the algorithm the key issue is determination of the slopes s_k so that the interpolation function values do not overshoot the values of measured data.

Let's consider two points $P_k(x_k, y_k)$ and $P_{k+1}(x_{k+1}, y_{k+1})$ being the breakpoints between which the interpolation should be proceeded. The divided difference b_k is defined as:

$$b_k = \frac{y_{k+1} - y_k}{d_k}. \tag{1}$$

While the length of the k-th subinterval d_k is:

$$d_k = x_{k+1} - x_k . \tag{2}$$

At the interior breakpoints, if b_k and b_{k-1} have the same sign and the two intervals have the same length, the reciprocal slope of the Hermite interpolant is the average of the reciprocal slopes of the piecewise linear interpolant on either side:

$$s_k = \frac{b_{k-1} b_k}{0,5\left(b_{k-1} + b_k\right)} , \tag{3}$$

where:

s_k -slope of the interpolant at the x_k .

In case of the same sign of b_k and b_{k-1}, at the same time having different lengths, another approach should be considered. The slope s_k is a weighted harmonic mean, with weights determined by the lengths of the two intervals:

$$\frac{l_1 + l_2}{s_k} = \frac{l_1}{b_{k-1}} + \frac{l_2}{b_k} , \tag{4}$$

where:

$$l_1 = 2d_k + d_{k-1} ,\ l_2 = d_k + 2d_{k-1} \tag{5}$$

The slopes at either end of the data interval are determined by a slightly different, one-sided analysis. And the extrapolation is also applied to fully exploits all available data.

4. UAV MODEL FOR MEASUREMENT ERROR IDENTIFICATION

To identify measurement errors, the kinematic formulation of the airplane model is used. The airplane equations of motion [3, 10] are reformulated in order to use the translational acceleration instead of applied forces in g units. That leads to equation system in body –axis , in which only kinematic quantities are exploited. The kinematic equations are composed of the translational equations of motion, the rotational kinematic equations, and the navigation equations.

The states $\mathbf{x}$ of the airplane are :

$$\mathbf{x} = [\, u \quad v \quad w \quad \phi \quad \theta \quad \psi \quad x_E \quad y_E \; h \,], \tag{6}$$

where:
u , v , w - translational velocities,

θ , ψ , ϕ -pitch, yaw, roll angle respectively.

The outputs $\mathbf{y}$ of the model are:

$$\mathbf{y} = [\, q_d \;\; h \;\; \alpha \;\; \phi \;\; \theta \;\; \psi \,], \tag{7}$$

where:
q_d - dynamic pressure,
h - altitude,
α - angle of attack.

The input signals $\mathbf{i}$ of the model are : ax, ay, az, p, q, r

$$\mathbf{i} = [\, a_x \;\; a_y \;\; a_z \;\; p \;\; q \;\; r \,], \tag{8}$$

where:
a_x, a_y, a_z - translational accelerations,
p, q, r -roll, pitch, yaw rate.

The identification concept differs to those applied in case of model parameter identification of an airplane, which usually concerns estimation of aerodynamic coefficient values. The input signals to the model are measured accelerations (a_x, a_y, a_z) and the angular rates (p, q, r).

The identified parameters corresponding to instrumentation errors are:

$$\boldsymbol{\theta} = [\, m_{a_x} \;\; m_{a_y} \;\; m_{a_z} \;\; m_p \;\; m_q \;\; m_r \,], \tag{9}$$

where:
m_{a_x} m_{a_y} m_{a_z} - instrumentation errors of accelerometers mounted along Ox,Oy,Oz body-axis respectively,

m_p m_q m_r - instrumentation errors of gyroscopes mounted along Ox,Oy,Oz body-axis respectively.
The UAV model has a form of coupled, nonlinear first order Ordinary Differential Equations and may be formulated in state-space form, in which state and output equations are distinguished:

State equation:

$$\dot{\mathbf{x}} = \mathbf{f}\left(t, \mathbf{x}, \mathbf{i}, \boldsymbol{\theta}\right), \tag{10}$$

Output equation:

$$\mathbf{y} = \mathbf{g}\left(t, \mathbf{x}, \mathbf{i}, \boldsymbol{\theta}\right). \tag{11}$$

As long as the measurement noise on the accelerations and angular rates is relatively small and zero mean, the numerical solution of the kinematic equations is not affected significantly by this process noise.

5. APPLIED IDENTIFICATION PROCEDURE

The UAV model parameters $\boldsymbol{\theta}$ are identified using the identification procedure which aim is to minimize the model errors $\mathbf{e}(t_k)$ defined as a differences between measurements (observations) $\mathbf{z}(t_k)$ and model outputs $\mathbf{y}(t_k)$. It is based on minimization of the following cost function negative logarithm:

$$J(\boldsymbol{\theta},\mathbf{R})=\frac{1}{2}\sum_{k=1}^{N}\left[\mathbf{e}(t_k)\right]^T\mathbf{R}^{-1}\left[\mathbf{e}(t_k)\right]+\frac{N}{2}\ln\left[\det(\mathbf{R})\right]+\frac{Nn_y}{2}\ln(2\pi) \tag{12}$$

where:

R-errors covariance matrix.

Model errors $\mathbf{e}(t_k)$ at different time points are statistically independent and they are assumed to be distributed with zero mean and covariance matrix **R:**

$$E\left\{\boldsymbol{\varepsilon}(t_k)\right\}=0\,; \tag{13}$$

$$E\left\{\boldsymbol{\varepsilon}(t_k)\boldsymbol{\varepsilon}^T(t_l)\right\}=\mathbf{R}\cdot\delta_{kl} \tag{14}$$

There is only measurement noise in the system, the process noise is neglected.

Using relaxation strategy and quazi-linearization optimization method [4] is a key to obtain accurate estimates of parameters values. The quasi-linearization is a first order approximation to the system responses around some nominal value $\boldsymbol{\theta}_0$, which can be written in a form:

$$\mathbf{y}(\boldsymbol{\theta})=\mathbf{y}(\boldsymbol{\theta}_0+\Delta\boldsymbol{\theta})\approx\mathbf{y}(\boldsymbol{\theta}_0)+\frac{\partial\mathbf{y}}{\partial\boldsymbol{\theta}}\cdot\Delta\boldsymbol{\theta} \tag{15}$$

The output of the model $\mathbf{y}(\boldsymbol{\theta})$ may be then substituted by the quasi-linearized form presented above with dropped argument $\boldsymbol{\theta}_0$.

Together with relaxation technique, it leads to obtaining system of linear equations:

$$\boldsymbol{\theta}_{i+1}=\boldsymbol{\theta}_i+\Delta\boldsymbol{\theta}, \tag{16}$$

$$\mathbf{F}\cdot\Delta\boldsymbol{\theta}=-\mathbf{G}\,, \tag{17}$$

where:

$$\mathbf{F}=\sum_{k=1}^{N}\left[\frac{\partial\mathbf{y}(t_k)}{\partial\boldsymbol{\theta}}\right]^T\mathbf{R}^{-1}\left[\frac{\partial\mathbf{y}(t_k)}{\partial\boldsymbol{\theta}}\right], \tag{18}$$

$$\mathbf{G}=-\sum_{k=1}^{N}\left[\frac{\partial\mathbf{y}(t_k)}{\partial\boldsymbol{\theta}}\right]^T\mathbf{R}^{-1}\left[\mathbf{z}(t_k)-\mathbf{y}(t_k)\right], \tag{19}$$

and

i -iteration index,

G -the gradient matrix,

F -the symmetric, positive-defined information matrix (Hessian).

The linear equation system is solved using LU decomposition. The outputs $\mathbf{y}(t_k)$ are determined solving the UAV model equation system by Gear method [8]

6. RESULTS

The identification procedure described above is implemented in Matlab environment as well as airplane kinematic model. The UAV Cularis data from flight tests are used for identification of parameters corresponding to instrumentation errors. Identified parameters are then introduced to the model state and output equations in order to calculate outputs. Model outputs are subsequently compared to observations (data gathered during flight- tests). The difference between real data and outputs form simulated model has such small value that in case of every of six outputs $\mathbf{y}$, it is almost invisible on the diagrams. Two linear in different colors, represent observations $\mathbf{z}$ (colore blue) and model outputs $\mathbf{y}$ (color orange) overlap (Fig. 3).

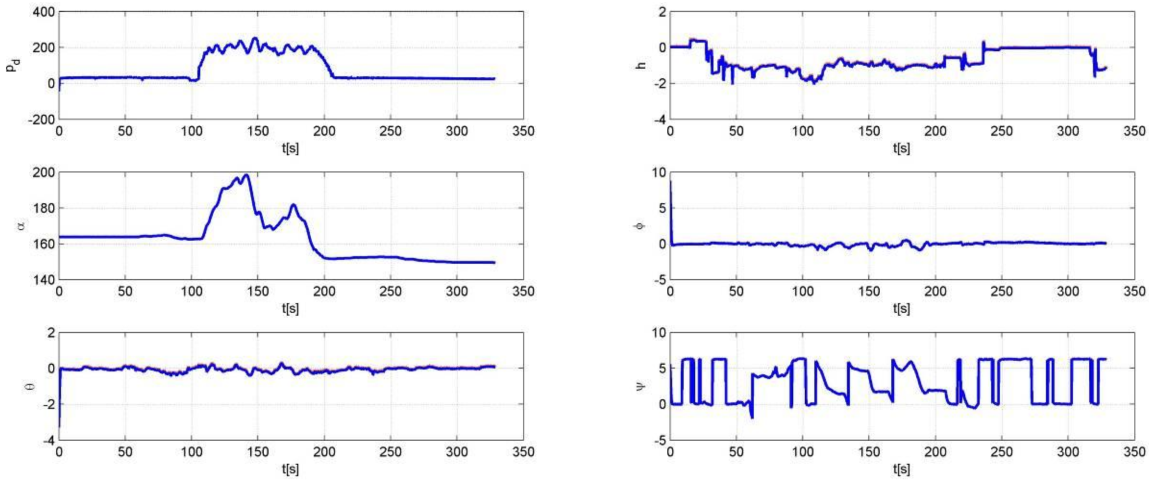

Fig.3. Comparison of UAV simulated model outputs and observations gathered during flight- tests

7. CONCLUSIONS

In the paper identification of measurement errors applied to UAV Cularis flight-test data is presented. Data preparation for identification process is considered as it often decides of the successful identification. The problem of data synchronization is solved on the signal processing level by introducing interpolation procedure before applying identification algorithm. The identification method based on quazi-linearization optimization technique together with relaxation strategy is implemented in Matlab environment in order to pursue simulation tests. The nonlinear airplane equations of motion are formulated in body –axis and only kinematic quantities are exploited. The preliminary simulation test results indicates successful identification of measurement errors. Further research will focus on identification of the UAV aerodynamic coefficient on the basis of preprocessed data without measurement errors.

8. REFERENCES

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