SECTION 4

CONTROLLING THE AEROSPACE CRAFT, MARINE VESSELS AND OTHER MOVING OBJECTS

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NEURAL NETWORK APPROACH TO DIRECT PARAMETER ADAPTATION OF LONGITUDINAL AUTOPILOTS

Abstract. An improvement of longitudinal autopilots consisting of the digital PI and P controllers is addressed in this paper. In order to achieve a good performance of these autopilots a direct adaptation of their three parameters is proposed. To this end, the two-circuit feedback is added by the feedforward circuit containing a neural network which needs to be trained offline. The input signals of this neural network correspond to the airspeed and the altitude of an aircraft whereas its output signals are the three controller parameters to be adjusted if flight regime changes. The behavior of a new longitudinal autopilot is studied by simulation experiments.

Keywords: aircraft, longitudinal autopilot, flight regime, parameter adaptation, neural network.

Last time, the autopilots are designed by using the digital controller standard of P- and PI-type. To optimize their parameters, novel approaches taken from modern control theory are utilized. In particular, the so-called l_1-approach to choose the parameters of the digital lateral autopilot has been advanced in our paper [1]. Similar approach may also be proposed for the parameter adjustment of the digital longitudinal autopilots. Unfortunately, it is admissible if the flight conditions do not change. Nevertheless, when these conditions (the airspeed and the aircraft altitude) are varied then these controller parameters do not remain optimal.

The main contribution of this paper is a new method making it possible to directly adapt the autopilot parameters to the variation of the flight regime.

It is assumed that, for each fixed flight condition, the longitudinal motion of some aircraft can be described (after linearization) by the transfer function

$$W(s) := \frac{\dot{\vartheta}(s)}{\delta_e(s)} = \frac{K(s+a_1)}{s^2 + b_1 s + b_2} \tag{1}$$

relating the output that is the pitch rate, $\dot{\vartheta}(t) = L^{-1}\{\dot{\vartheta}(s)\}$ to the input that is the elevator defection, $\delta_e(t) = L^{-1}\{\delta_e(s)\}$. In this expression, K denotes the gain, and a_1, b_1 and b_2 represent some coefficients. It is essential that as K as these coefficients depend on the flight regime.

The problem stated in this paper is to adjust the two parameters k_P^{in}, k_I^{in} of PI controller and the one parameter k_P^{ex} of P controller when the flight conditions change.

A key idea advanced in solving this problem is that there exist some *a priori* unknown (may be, complex enough) functions

$$\left.\begin{aligned} k_{\mathrm{P}}^{\mathrm{in}} &= \varphi_1(V, h), \\ k_{\mathrm{I}}^{\mathrm{in}} &= \varphi_2(V, h), \\ k_{\mathrm{P}}^{\mathrm{ex}} &= \varphi_3(V, h), \end{aligned}\right\} \tag{2}$$

where V and h denote the airspeed and the aircraft altitude, respectively. They should be approximated by suitable neural networks

$$\Phi_i(V, h, w_{\mathrm{i}}) \tag{3}$$

with weight vectors w_{i} such that

$$|\varphi_i(V, h) - \Phi_i(V, h, w_{\mathrm{i}})| \le \varepsilon \tag{4}$$

for given $\varepsilon > 0$ and each $i = 1, 2, 3$.

In order to search w_{i}s satisfying (4), the standard recursive offline learning algorithms similar to that in [2, 3] are needed. To this end, a finite set of training examples corresponding to the different flight regimes is formed. This set is obtained as follows.

First, for each separate regime we determine K, and the coefficients a_1, b_1 and b_2 appearing in (1). Second, for each $W(s)$, the optimal components of the three-dimensional controller parameter vector $k_{\mathrm{c}}^* = [k_{\mathrm{P}}^{\mathrm{in}}, k_{\mathrm{I}}^{\mathrm{in}}, k_{\mathrm{P}}^{\mathrm{ex}}]^T$ is calculated as

$$k_{\mathrm{c}}^* = \arg\min_{k_{\mathrm{c}}} \| W(k_{\mathrm{c}}) \|_1,$$

where $\| W(k_{\mathrm{c}}) \|_1$ denotes the l_1-norm of the discrete-time transfer function $W(z^{-1}, k_{\mathrm{c}})$ from a disturbance (e.g., wind gust) to the variation of the current pitch altitude $\vartheta(t)$ from its desired value.

Thus, a number of pairs $\{[V, h], k_{\mathrm{c}}\}$ are used to train offline the neural networks (3).

After stopping the learning algorithm, instead of unknown function given by (2), the three neural networks giving

$$\left.\begin{aligned} k_{\mathrm{P}}^{\mathrm{in}} &= \Phi_1(V, h, w_1), \\ k_{\mathrm{I}}^{\mathrm{in}} &= \Phi_2(V, h, w_2), \\ k_{\mathrm{P}}^{\mathrm{ex}} &= \Phi_3(V, h, w_3) \end{aligned}\right\} \tag{5}$$

can be employed to determine the current optimal parameters of the autopilot.

To implement (5), an information with respect to the current airspeed and the aircraft altitude is needed.

We can conclude that the proposed approach makes it possible to achieve the accuracy of pitch stabilization which is better than in existing autopilots.

References

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