Precise Takagi-Sugeno fuzzy logic system for UAV longitudinal stability: an Industry 4.0 case study for aerospace

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ABSTRACT

Industry 4.0 is making inroads even into the field of aerospace, which is extremely conservative due to the safety concerns involved with the introduction of new technology. We used fuzzy logic to create a very reliable simplification and reduce the complexity of the critical longitudinal stability equations for a flying wing drone. Our approximate method allowed us to have a very light calculation effort at the price of a negligible error in terms of the size and dynamics of the craft, thus reducing the work required by the telecommunication segment that manages the takeoff and landing manoeuvres.

1. INTRODUCTION

The authors have been involved in the development of a fixed wing tailless drone (UAV). We will examine the critical challenge of maintaining longitudinal stability that confronts aircraft with this design [1]-[3].

In the next sections, we will briefly illustrate the type of hardware that was chosen, and, after discussing the aerodynamic challenges, we will address the fuzzy logic resolution method that was used to simplify the calculations. In the current context of flight in which the ground, air and space segments must converse with each other, the ground segment, thanks to Internet-of-Things (IoT) and Wi-Fi technology, is taking on an increasingly important role for UAVs during flight phases and landing via the base station [4].

We can therefore say that Industry 4.0 is making inroads even into the extremely conservative and slow-to-change field of aerospace. This reluctance to change is, of course, due to a key aspect of both air and spaceflight: safety. It took decades of testing and certification to entrust an airliner to the autopilot, and even now, the cabin must be staffed by a human pilot. Contrary to popular belief, safety is not less important in drones, even though there are no people on board. In the case examined in this paper, we entrust the control of longitudinal stability to an automatic system that, far from behaving like a simple machine, uses fuzzy logic to approach human behaviour, while still avoiding human weaknesses [5].

1.1. State of the Art

The flying wing design (i.e., an aircraft without horizontal empennage) was among the first to appear in the world of aviation; however, it was soon found to be intrinsically unstable. This instability leads to a loss of control if the flight is disturbed by a gust or a manoeuvre. Following the rapid development of aeronautical engineering in the early 1900s, the idea of tailless
aircraft took hold in the world of gliders. In particular, the Horten brothers developed an entire family of gliders of this type. This led to the study and use of special aerfoils optimised for this type of vehicle. After an uncertain start in the 1950s by Northrop Aviation (today Northrop-Grumman), the B-2 Spirit arrived in the late 1990s, an aerodynamically mature aircraft from all points of view. In the design of UAVs, the tailless formula was immediately successful, generating a series of models and strategies of use. Generally, they are engaged in missions in which aerobatics are clearly not the main requirement; indeed, stability is an essential feature in their use as aerial photogrammetric platforms. Due to the low drag, as has been noted, they are especially useful for surveillance tasks in temporally demanding missions. For this reason, the use of remote piloting is increasingly abandoned in favour of more tactical-operational autonomy. As a result, autonomous navigation systems that contain robust stability routines have been developed. Within this context, our work is aimed at proposing increasingly fast and efficient calculation methods.

2. THE SYSTEM

2.1. The UAV

The design (see Figure 1) of the drone is based on a flying wing; it is tailless with winglets at the wing tips and is energised by a pusher propeller. Such designs have extremely low aerodynamic induced resistance at the price of a strong criticality: poor longitudinal stability [6]-[8].

In order for the drone to be stable, it is necessary to manage the weight so that the centre of gravity is set lower than in a classically designed aircraft. Furthermore, there is always the danger that it can enter an uncontrollable aerodynamic state outside the flight envelope and fall into a ‘dead leaf’ condition, which is completely uncontrollable and inevitably leads to the loss of the drone [9]-[11].

2.2. The Flight Control System (FCS)

The Flight Control System (FCS) is the heart of the navigation system: it manages the attitude of the craft, the data coming from the payload and all communications. In order to develop a fast processor for the FCS, our attention was focused immediately on two main problems: firstly, we needed to calculate large volumes of parallel data with a single device; and secondly, we needed an accurate evaluation of approximated stability functions in order to increase the calculation speed.

As stated, the main tasks of the FCS are three: housekeeping (attitude control), data handling from the payload and telecommunications management. The innovation consists in not using three separate microprocessors for all functions but instead wrapping them all into one positively reprogrammable microprocessor.

2.3. The IoT system

In this section, we will examine UAV navigation within the IoT network (see Figure 2). The UAV receives position signals from the Global Navigation Satellite System (GNSS) constellation, processes them for navigation and then uses telemetry to transmit data to the tracking system [12].

The tracking system consists of a high gain antenna (used to extend the range) that collects the signals and sends them to the server. The server has the task of managing and sorting the signals and sending them to the operator [13].

On the landing strip, meanwhile, equipment is available that uses a camera to detect the state of the track and meteorological information, which will then be transmitted via Wi-Fi to the aircraft as it approaches the runway [14].

The advantage of this system is clear: non-essential flight data are not transmitted, keeping the communication systems clear. In Europe, the IEEE 802.15.2 standard assigns the frequency of 868.3 MHz to Telemetry and Telecommands (TTC) for UAV. Since the communication channel is limited, saturating it is extremely easy, regardless of the type of modulation chosen [15].

2.4. Fuzzy Systems

Currently, fuzzy logic-based systems are among the most important applications of fuzzy logic in soft computing and applied mathematics, and they are widely used for solving control problems in all aspects of engineering [16]-[21]. The popularity of fuzzy logic-based systems is due to their ability to appropriately simulate human thinking, surpassing the limits of Boolean logic and expressing the system in its full complexity. The Takagi-Sugeno model (T-S), represented by the fuzzy relation ‘IF-THEN’, manages to describe a non-linear dynamic system with a linearised model that meets all the conditions set and has a negligible error rate that will be shown at the end of the paper [22]-[27]. The logical processes that lead to the formulation of the inference conditions are as follows: firstly, the logical process must undergo fuzzification, a modelling based on the rigorous application of fuzzy (not Boolean) rules; and finally, the whole linear system must be defuzzified to return to the physical world [28].

2.5. Fuzzy Systems Algebra

For clarity of exposition, we will briefly introduce the fuzzy algebra method that we used [29]-[34].

Consider a fuzzy set \( \Phi_{ij} \) composed of:

\[
\begin{align*}
\zeta_1(t) &= \Phi_{11} \\
\zeta_2(t) &= \Phi_{12} \\
\zeta_3(t) &= \Phi_{13} \\
&\quad \ldots \ldots \ldots \ldots \\
\zeta_{p-1}(t) &= \Phi_{1(p-1)} \\
\zeta_p(t) &= \Phi_{1p}
\end{align*}
\]

For the model rule, \( i^{th} \), we have a set of \( r \) model rules, and then we have:

\[ \zeta_p(t) = \text{input vector} \]

\[ x(t) = \text{state vector} \]
\[ \xi_p(t) = \text{output vector} \]

The complete rule now is:

IF \( z_i(t) = \Phi_{i1} \) AND \( z_2(t) = \Phi_{i2} \) AND ... AND \( z_p(t) = \Phi_{ip} \)

THEN 
\[ \dot{x}_i(t + 1) = \mathcal{A}_i x_i(t) + \mathcal{B}_i \xi_p(t) \]
\[ y(t) = c_i x_i(t) \]

with \( i = 1, 2, \ldots r \)

where
\[ \mathcal{A}_i = \begin{pmatrix} \xi_{i1} & \cdots & \xi_{ip} \\ \vdots & \ddots & \vdots \\ \xi_{ip} & \cdots & \xi_{pp} \end{pmatrix} \]

\( \mathcal{A}_i \) is the matrix (square) with the real elements and \( x_1(t), x_2(t), \ldots, x_p(t) \) are known premise variables.

Each subsystem is represented by a linear equation:
\[ \mathcal{A}_i x_i(t) + \mathcal{B}_i \xi_p(t). \]

Now for the model we have:
\[ x_i(t + 1) = \frac{\sum_{i=1}^{r} \xi_i[z(t)] \mathcal{A}_i x_i(t) + \mathcal{B}_i \xi_p(t)}{\sum_{i=1}^{r} \xi_i[z(t)]}. \]

Simplifying:
\[ x_i(t + 1) = \sum_{i=1}^{r} h_i[z(t)] \mathcal{A}_i x_i(t) + \mathcal{B}_i \xi_p(t). \]

So, according to (6)
\[ \xi_p(t) = \sum_{i=1}^{r} h_i[z(t)] \mathcal{A}_i x_i(t) + \mathcal{B}_i \xi_p(t). \]

Then we have:
\[ \xi_p(t) = \frac{\sum_{i=1}^{r} h_i[z(t)] \mathcal{A}_i x_i(t)}{\sum_{i=1}^{r} h_i[z(t)]}. \]

The expression of \( \xi_i \) is:
\[ \xi_i[z(t)] = \prod_{j=1}^{p} \Phi_{ij}[z_j(t)]. \]

Then:
\[ h_i[z(t)] = \frac{\xi_i[z(t)]}{\sum_{i=1}^{r} \xi_i[z(t)]}. \]

The membership of \( z_j(t) \) in \( \Phi_{ij} \) is:
\[ \sum_{i=1}^{r} \xi_i[z(t)] > 0 \]
\[ \xi_i[z(t)] \geq 0, \text{ with } i = 1, 2, \ldots r. \]

We have
\[ \sum_{i=1}^{r} h_i[z(t)] = 1 \]
\[ h_i[z(t)] \geq 0, \text{ with } i = 1, 2, \ldots r. \]

for all \( t \).

### 3. FUZZY STABILITY

#### 3.1. Fuzzy Model Application

For the longitudinal stability interval of the drone, we now have the following system:

\[ \dot{x}_V = v \]
\[ L_w \equiv \frac{1}{2} v^2 \alpha_w \]

where
\[ v_{\text{min}} < v \leq v_{\text{max}} \]

\[ v_{\text{min}} = \text{minimum allowed speed (} = v_{\text{stall}}) \]
\[ v_{\text{max}} = \text{maximum allowed speed according to the linearity interval.} \]

So (15) becomes:
\[ \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} \dot{x}_V \\ L_w \end{bmatrix} = \begin{bmatrix} 1 \\ v^2 \alpha_w \end{bmatrix}. \]

(17)

The fuzzy variables \( v \) and \( \alpha_w \) are nonlinear terms in the expressions.

Posing \( z_1 \) and \( z_2 \) as premise variables that may be functions of state variables,
\[ \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = \begin{bmatrix} v^{2} \alpha_w \\ \frac{1}{2} v^2 \alpha_w \end{bmatrix} \]

we can express (17) as:
\[ \begin{bmatrix} 1 \\ v^2 \alpha_w \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}. \]

Now we should calculate the minimum and maximum of the parameters:
\[ \begin{bmatrix} v_{\text{stall}} \\ v_{\text{max}} \end{bmatrix} = \begin{bmatrix} -4 \\ 8 \end{bmatrix}. \]

Therefore, expanding (19), we have the limits:
\[ \begin{bmatrix} v_{\text{min}} \\ v_{\text{max}} \end{bmatrix} = \begin{bmatrix} 8 v_{\text{max}} \\ -4 \end{bmatrix}. \]

Therefore \( v \) and \( \alpha_w \) can be represented by membership functions \( M_1, M_2, N_1 \) and \( N_2 \) as follows:
\[ z_1 = M_1(z_1) \cdot (8 v_{\text{max}}) + M_2(z_1) \cdot (-4 v_{\text{stall}}) \]
\[ z_2 = N_1(z_2) \cdot \left( \frac{1}{2} v^2 \alpha_w \right) + N_2(z_2) \cdot \left( \frac{1}{2} v_{\text{stall}} \right) \]
where
\[
\begin{align*}
(M_1(z_1) + M_2(z_1)) &= 1 \\
(N_1(z_2) + N_2(z_2)) &= 1
\end{align*}
\]  
(24)

Now we introduce the model rule. This is the liaison between real physical elements and the limits.

#1: IF z₁ is 'high' AND z₂ is 'big' THEN \( \dot{x}_V = A_1 \cdot x_V \)

#2: IF z₁ is 'high' AND z₂ is 'small' THEN \( \dot{x}_V = A_2 \cdot x_V \)

#3: IF z₁ is 'low' AND z₂ is 'big' THEN \( \dot{x}_V = A_3 \cdot x_V \)

#4: IF z₁ is 'low' AND z₂ is 'small' THEN \( \dot{x}_V = A_4 \cdot x_V \)

where for the \( A_i \) parameter we have:

\[
A_1 = \begin{bmatrix}
\max z_1 & \max z_2 \\
\max z_1 & \max z_2
\end{bmatrix} = \begin{bmatrix}
1 & 0 \\
0 & \frac{1}{2} v_{\text{max}}^2
\end{bmatrix}
\]  
(25)

\[
A_2 = \begin{bmatrix}
\max z_1 & \max z_2 \\
\max z_1 & \max z_2
\end{bmatrix} = \begin{bmatrix}
0 & 1 \\
1 & \frac{1}{2} v_{\text{stall}}^2
\end{bmatrix}
\]  
(26)

\[
A_3 = \begin{bmatrix}
\max z_1 & \max z_2 \\
\max z_1 & \max z_2
\end{bmatrix} = \begin{bmatrix}
0 & 1 \\
1 & \frac{1}{2} v_{\text{max}}^2
\end{bmatrix}
\]  
(27)

\[
A_4 = \begin{bmatrix}
\max z_1 & \max z_2 \\
\max z_1 & \max z_2
\end{bmatrix} = \begin{bmatrix}
0 & 1 \\
1 & \frac{1}{2} v_{\text{stall}}^2
\end{bmatrix}
\]  
(28)

Now, \( \dot{x}_V \) can be derived from the defuzzification process as:

\[
\dot{x}_V = h_1(z) A_1 \cdot x_V + h_2(z) A_2 \cdot x_V + h_3(z) A_3 \cdot x_M + h_4(z) A_4 \cdot x_V
\]  
(29)

in which

\[
\begin{align*}
h_1(z) &= M_1(z_1) \times N_1(z_2) \\
h_2(z) &= M_1(z_1) \times N_2(z_2) \\
h_3(z) &= M_2(z_1) \times N_1(z_2) \\
h_4(z) &= M_2(z_1) \times N_2(z_2)
\end{align*}
\]  
(30)

This fuzzy model exactly represents the nonlinear system in the region \([v_{\text{stall}} v_{\text{max}}] \times [-4^\circ 8^\circ]\) in the \( v, \alpha_w \) space.

As is evident in equations (29) and (30), the responses of the fuzzy model can exactly follow the responses of the original equations, which means the fuzzy model can exactly represent the original system in the pre-specified domains. That is to say, inside of the boundaries of \( v \) and \( \alpha_w \) the above approach can accurately represent the original system. The advantage of this method is immediate: the calculation effort is enormously decreased. In practice, everything is resolved through linear systems or simple multiplication between square matrices.

3.2. The simulation

The simulation was performed with the combined Matlab®/Simulink® tool, and the results were validated separately on a sample of 44 specific points.

The difference between a classical solution and a fuzzy one is simple: a classical set contains elements that satisfy precise properties of membership, while a fuzzy set contains elements that satisfy imprecise properties of membership. Figure 3 illustrates the fuzzification procedure for the problem, which may be defined as transforming the available data from a crisp set into a fuzzy set. Basically, this operation translates accurate crisp input values into linguistic variables. For this, it is necessary to define the rules, the membership functions, and the architecture. Subsequently, thanks to the T-S method (as explained above), a mathematical result is reached.

Figure 4 illustrates the data evaluation process. Initially, a rather large set of real data obtained from tests on real drones (about 13 Gb) was produced. These were processed in parallel both with the fuzzy method and with the system method of equations. Since we knew the solution, we could therefore establish the percentage of error introduced in each method. Obviously and as expected, the second provides less approximate data but requires much more calculation. To determine the difference, each solution was associated with a marker providing the calculation time. At the end of the process, we added up the time data and found that, on average, the T-S method reduced calculation time by 83.7% for each cycle, thus allowing for much faster physical feedback. This speed is paid for with greater error, as we will see in the next paragraph, but the error is always within an absolutely acceptable range for our navigation system.

3.3. The error

Figure 5 shows the results of our work, with the blue line representing the percentage error of the approximate solution. Takagi-Sugeno is traced with respect to the ‘exact’ solution that was calculated with recursive and time-consuming numerical methods. For completeness, we have also included the generated simulation of the completed aircraft (red line). The green line indicates the difference between the two. The excellent behaviour of the T-S approximation within the nonlinearity interval.
\(-4^\circ \leq \alpha_w < 8^\circ\) is immediately visible, although it decays rapidly outside this non-linear characteristic.

4. CONCLUSIONS

In a more dynamic context, the execution speed of the algorithms as well as the structure or shape of drones helps to make some critical manoeuvring phases more agile by drastically reducing the computational cost of the analysis (see Figure 5). For this reason, we feel our work is justified.

The drone used in our case study was a fixed-wing UAV that required micro-tapping of all ancillary and non-viable systems. Fuzzy logic was used to reduce the complexity of the longitudinal stability equations, which are critical for flying wings, and thus reduce the computational load on the FCS.

Our approximate calculation method allowed us to have a very light calculation effort at the price of a negligible error in terms of the size and dynamics of the craft.

APPENDIX A: The Horten Aerofoil

We chose the Horten \((l/c = 11\% \text{, } f/l = 2\%)\) non-symmetrical aerofoil. It behaves quite well aerodynamically in the expected speed range, with a stall preceded by buffeting at a reasonably low stall speed (see Figure 6a and 6b).

In order to move the aerodynamic centre backwards, a 30-degree sweep angle was chosen, resulting in a CG that was not too far forward but provided a noticeable decrease in drag [35]. For reference, we will consider the aerofoil to which the lift force of the wing is applied (ideally). This aerofoil was originally designed and used by the Horten brothers, who built a number of high-performance sailplanes during the 1930s and 1940s. Their designs are legendary, although some of their published performance data are a little too good [36].

Their planes were well known for their good handling characteristics, which could be of greater importance than the actual performance figures from our project [37].

A.1 The Longitudinal Stability

For the balance of the forces around the Y-axis we have (see Figure 7):

\[
M_{cgw} = L_w \cos(\alpha_w - i_w) \cdot (x_{cg} - x_{ac}) \\
+ D_w \sin(\alpha_w - i_w) \cdot (x_{cg} - x_{ac}) \\
+ L_w \sin(\alpha_w - i_w) \cdot (z_{cg} - z_{ac}) \\
+ (-D_w)(\alpha_w - i_w) \cdot (z_{cg} - z_{ac}) + M_{acw}
\]  

(31)

where

\[ M_{cgw} = \text{moment of all the wing forces around the centre of gravity} \]
\[ L_w = \text{lift force of the wing} \]
\[ D_w = \text{drag force of the wing} \]
\[ \alpha_w = \text{angle between the main chord and the wind direction (angle of attack)} \]
\[ i_w = \text{angle between the main chord and the X-axis} \]
\[ x_{cg} = \text{distance of centre of gravity from the Z-axis} \]
\[ x_{ac} = \text{distance of aerodynamic centre of gravity from the Z-axis} \]
\[ z_{cg} = \text{distance of centre of gravity from the X-axis} \]
\[ z_{ac} = \text{distance of aerodynamic centre from the X-axis} \]
\[ M_{acw} = \text{moment of all the wing forces around the aerodynamic centre} \]
\[ C.G. = \text{centre of gravity} \]
\[ A.C. = \text{aerodynamic centre} \]

Now we consider that if the angle of attack is reasonably small, the lift is much less than the drag:

\[ L_w \gg D_w \]  

(32)

and for small angles:

\[ \alpha_w - i_w \ll 1 \]  

(33)
The expression for the lift \( L \) is:

\[
L = \frac{1}{2} \rho v^2 S C_L.
\]

Applying this to (39), we have:

\[
\frac{1}{2} \rho v^2 S C_L = \frac{M_{Cw}}{x_{cg} - x_{ac}} - \frac{M_{acw}}{x_{cg} - x_{ac}}.
\]

We can linearise equation (40), and we have:

\[
L_w = \frac{1}{2} \rho v^2 S k \alpha_w.
\]

Posing:

\[
\mathbb{F} = \rho k S
\]

we have:

\[
L_w = \frac{1}{2} v^2 \mathbb{F} \alpha_w.
\]

This is the equation set considered in paragraph 3.1.

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Figure 7. Force balance around the Y-axis.

Figure 8. Horton \((t/c = 11\% , f/c = 2\%\) aerofoil \(C_L\) vs. \(\alpha\), characteristics \((Re = 10^7 \cdot 8.5 \times 10^5)\): the linear interval is evidenced in red.
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