Merging fuzzy observer-based state estimation and database classification for fault detection and diagnosis of an actuated seat

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Merging Fuzzy Observer-based State Estimation and Database Classification for Fault Detection and Diagnosis of an Actuated Seat

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***Abstract*—This paper proposes an approach for Fault Detection and Diagnosis (FDD) of an actuation system for passengers seats in commercial aircrafts. The FDD is performed using classification algorithms. The supervised classification algorithms are usually based on data collected from the different sensors installed on a real system. Thus, to reduce the number of embedded sensors and so the costs of seat components in commercial aircrafts, a fuzzy Takagi-Sugeno (T-S) state observer is considered to estimate non-measured state variables in order to enrich the database used for the supervised classification process. From experimental measurements on a prototype of the actuated seat, the benefit of adding T-S observer-based estimations is illustrated through a comparison of the classification results obtained using databases without then with estimated data.**

I. Introduction

The increasing complexity of industrial systems and their related operational requirements have induced the necessity to develop reliability and safety techniques in order to ensure the availability of these systems at all times. To achieve this goal, FDD methods are required in order to detect all kind of faults that may occur on the system [1, 2, 3, 4, 5]. These faults may lead to critical behavior, which necessitate urgent and expensive maintenance operations.

In this study, we are interested in FDD of actuated seats for commercial aircrafts produced by Zodiac Seat Actuation & Control (ZSAC), which is a world leader in aerospace equipment designs. The objective is twice: 1) reducing the number of sensors to reduce the cost of such commercial embedded components, 2) improving the FDD in order to reduce the time of maintenance, repair and overhaul operations, and so their costs.

During the last decades, there has been an increasing interest in FDD methods, which can be divided in two families: data-driven methods and model-based ones. Data-driven methods are mainly based on data collected from the real system, see e.g. [5, 6, 7]. The advantage of such FDD approaches is their low computational cost requirement, making them appealing for complex embedded systems. On the other hand, model-based methods are advantageous when we do not have sufficient collected data. They are often based on soft sensors, also known as observers, designed from an analytical model of the physical behavior of the considered system, see e.g. [8, 9, 10, 1, 11]. Note that each of these FDD families has its own advantages and drawbacks, and no one can address all FDD requirements. Thus, the design of hybrid approaches, merging various methods might be promising. Few recent works were done for this kind of problems [12, 13, 14, 15]. Nevertheless, their application to industrial processes remain challenging.

In our previous paper [16], one has proposed a supervised classification approach for FDD merging the data collected from real measurements and the ones obtained from linear state observer estimations. However, the linear observer was designed from the dynamical model of the seat, which is naturally nonlinear. Therefore, the designed linear observer was valid around only one operating point. This constitutes a major drawback of this previous study since it can be argued that there was no guarantee of good state estimations for wide range movements of the seat. Therefore, this study aims at addressing this concern by designing a Takagi-Sugeno observer [17], valid on the whole operating space of the seat. Indeed, Takagi-Sugeno (T-S) fuzzy models [18] present the advantage of perfectly matching a nonlinear system on a compact set of its state space when they are obtained from the sector nonlinearity approach [19].

This paper is organized as follows. First, the considered actuated seat and his dynamical model will be presented. Then, a T-S model of the seat will be derived and a dedicated T-S observer will be synthesized. Then, the adopted data-driven FDD approach will be presented. Finally, from experimental measurements, a comparison of the FDD results obtained from the classification process without observer-based estimations, then with the previously considered linear observer [16], and finally with the proposed T-S observer, to illustrate the benefit of the latter.

II. Description and modelling of the considered actuated seat

This study consists in detecting and diagnosing the different faults on a prototype of an aircraft actuated seat presented in Fig. 1.

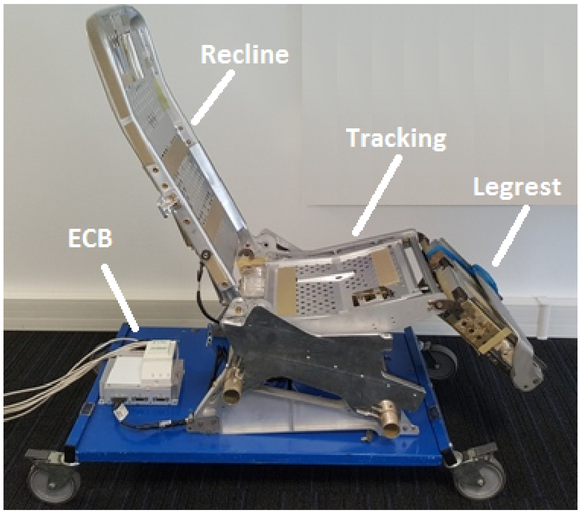

Fig. 1. Prototype of the considered actuated seat

The actuated seat is composed of three actuated bodies (recline, tracking and legrest). Each body is moved by an electrical actuator including a potentiometer which delivers the corresponding angular position. The actuators torques are controlled by the Electronic Control Box (ECB) such that the different segments track a constant speed, with respect to the passenger actions on a keypad (forward, backward, stop, etc.).

In order to save space in this paper, only the recline body will be considered in the sequel. It is modeled as an inverted pendulum actuated by an electromechanical actuator. Hence, its dynamical model can be obtained from the Lagrange formalism and is given by :

$$J\ddot{\theta}(t) - mgl\sin\theta(t) = u(t) \tag{1}$$

where $\theta(t)$ and $\ddot{\theta}(t)$ denote respectively the angular position and acceleration of the recline, $u(t)$ denotes the input torque, J=0.0108 ($kg.m^2$) is the inertia of the recline around its pivot axis, m=0.7 (kg) is the mass of the recline, l=0.33 (m) is the length of the recline and g=9.81 ($m.s^{-2}$) is the gravitational acceleration.

Therefore, from (1), a nonlinear state space model of the recline is given by:

$$\begin{cases} \dot{x}(t) = A(\theta(t))x(t) + Bu(t) \\ \theta(t) = Cx(t) \end{cases} \tag{2}$$

where $x(t) = [\theta(t) \quad \dot{\theta}(t)]^T$ is the state vector, $u(t)$ is the input torque, the angular position $\theta(t)$ is the measured output, $A(\theta(t)) \in \mathbb{R}^{2\times 2}$, $B \in \mathbb{R}^{2\times 1}$ and $C \in \mathbb{R}^{1\times 2}$ are the matrices describing the system dynamics, which are given by:

$$A(\theta(t)) = \begin{bmatrix} 0 & 1 \\ \frac{mgL}{J} \times \frac{sin\theta(t)}{\theta(t)} & 0 \end{bmatrix}, B = \begin{bmatrix} 0 \\ \frac{1}{J} \end{bmatrix}, C = \begin{bmatrix} 1 & 0 \end{bmatrix}$$

From now, the nonlinear state space of the recline being defined, the next section focuses on its T-S modeling and observer design.

III. T-S modelling and observer design

In this section, our goal is to derive a T-S model of the recline, then to design a dedicated T-S state space observer. The purpose of the use of this T-S observer is to estimate the angular velocity $\dot{\theta}(t)$, which is not measured from embedded sensors, then to use this estimation as a new attribute for the FDD classification process presented in the next section.

To obtain a T-S model of the recline, note that the nonlinear state space model (2) contains one nonlinearity:

$$f(\theta(t)) = \frac{sin\theta(t)}{\theta(t)} \tag{3}$$

which is bounded for all t and $\theta(t)$ such that $f(\theta(t)) \in [\underline{f}, \overline{f}]$ with $\underline{f} \simeq -0.2172$ and $\overline{f} = 1$.

Thus, by considering $\theta(t)$ as a premiss variable and by using the well-known sector nonlinearity approach [19], one can rewrite (3) as:

$$f(\theta(t)) = \frac{f(\theta(t)) - \underline{f}}{\overline{f} - \underline{f}} \times \overline{f} + \frac{\overline{f} - f(\theta(t))}{\overline{f} - \underline{f}} \times \underline{f} \tag{4}$$

From (4), one may define the following convex membership functions:

$$h_1(\theta(t)) = \frac{f(\theta(t)) - \underline{f}}{\overline{f} - \underline{f}} \tag{5}$$

$$h_2(\theta(t)) = \frac{\overline{f} - f(\theta(t))}{\overline{f} - \underline{f}} \tag{6}$$

Consequently, a two rules T-S fuzzy model which is exactly representing (2) is given in its compact form by:

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{2} h_i(\theta(t))A_i x(t) + Bu(t) \\ \theta(t) = Cx(t) \end{cases} \tag{7}$$

with:

$$A_1 = \begin{bmatrix} 0 & 1 \\ \frac{mgL}{J} \times \overline{f} & 0 \end{bmatrix}, A_2 = \begin{bmatrix} 0 & 1 \\ \frac{mgL}{J} \times \underline{f} & 0 \end{bmatrix}$$

From (7), our goal is now to design the following state space T-S observer given by:

$$\begin{cases} \dot{\hat{x}}(t) = \sum_{i=1}^{2} h_i(\theta(t)) \left(A_i\hat{x}(t) + Bu(t) + L_i\left(\theta(t) - \hat{\theta}(t)\right)\right) \\ \hat{\theta}(t) = C\hat{x}(t) \end{cases} \tag{8}$$

where $\hat{x}(t) = [\ \hat{\theta}(t) \quad \dot{\hat{\theta}}(t)\ ]^T$ denotes the estimated state vector and its estimated components $\hat{\theta}(t)$ and $\dot{\hat{\theta}}(t)$, L_i are the observer gain matrices to be synthesized.

From (7) and (8), the dynamic of the estimation error $e(t) = x(t) - \hat{x}(t)$ can be written as:

$$\dot{e}(t) = \sum_{i=1}^{r} h_i(\xi)(A_i - L_iC)e(t) \tag{9}$$

Thus, if one may synthesize the gain matrices L_i such that (9) is asymptotically stable, then the estimated state from the observer (8) converges asymptotically to the system state $x(t)$. This can be achieved by solving the Linear Matrix Inequalities (LMI) given in the following lemma.

Lemma 1. *[17] Let us consider the T-S model* (7) *and the observer* (8)*. The dynamics of the estimation error* (9) *is exponentially stable with a decay rate $\beta > 0$ if, for $i \in \{1, 2\}$, there exists the matrices N_i and $P = P^T > 0$ such that:*

$$A_i^T P + PA_i - C^T N_i^T - N_i C + 2\beta P < 0 \tag{10}$$

In that case, the changes of variables $N_i = P^{-1}L_i$ provide the gains of the T-S fuzzy observer.

Proof. Straightforward from [17] with B and C common matrices in the considered T-S model. □

By solving the LMIs presented in lemma 1 with the Matlab LMI toolbox [20] with $\beta = 5$ to ensure a fast convergence of the observer, the following gain matrices have been obtained:

$$L_1 = \left[\ 13.3764; 294.7022\ \right],\ L_2 = \left[\ 13.3764; 38.4599\ \right]$$

In order to validate the designed T-S observer and to compare it with the previously designed linear observer in [16], a simulation of the dynamical model of the recline (1) is performed from the erect position ($\theta = 0$) to the bed position ($\theta = \pi/2$), then back to the erect position. This simulation is plotted in Fig. 2. As one can notice, the designed T-S observer provide better estimates of the angular position and velocities than the linear observer. Indeed, the linear estimation error is bigger than the T-S-based estimation error. This confirm the superiority of the T-S observer for the considered application.

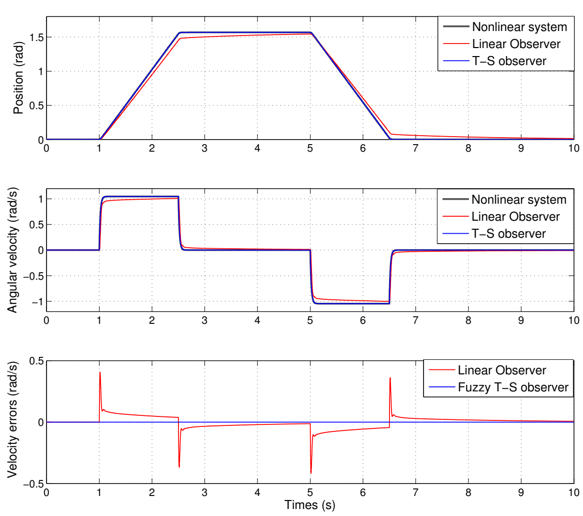

Fig. 2. Simulation of the state estimations: T-S observer vs Linear observer [16]

The T-S fuzzy observer being now designed, the next section will focus on the considered supervised classification approaches for FDD of the seat.

IV. Data-driven FDD

In this section, the goal is to apply a supervised classification [21, 22] for the FDD of the recline. Supervised classification necessitates 3 phases. The first one consists in constructing a database from measurements and observer-based estimations. Then, the constructed database will be partially used for the learning phase of the classifier. Finally, the remainder of the constructed database is used by the classifier during a test phase in order to validate the whole classification process. These steps are detailed in the sequel.

A. Database construction

Data processing is a very important step in classification issues. The construction of databases consists in collecting measured and estimated data at every sampling period in order to further use them in the learning and classification phases.

The seat is equipped by different sensors which measure the angular position of the recline and the electrical current of the actuator, which can be used to approximate the input torques. Moreover, the ECB provides the user's intentions (actions provided by the keypad) and their durations. These data will be enriched by the estimates of the angular velocity from the designed observer, and by an attribute related to the movement regularity rate, computed at the end of each movement (see [16] for more details).

Note that with the considered application, the sampling time for data processing is set to 300 ms. To illustrate the database construction, let us consider a fictive movement of the recline presented in Fig. 3.

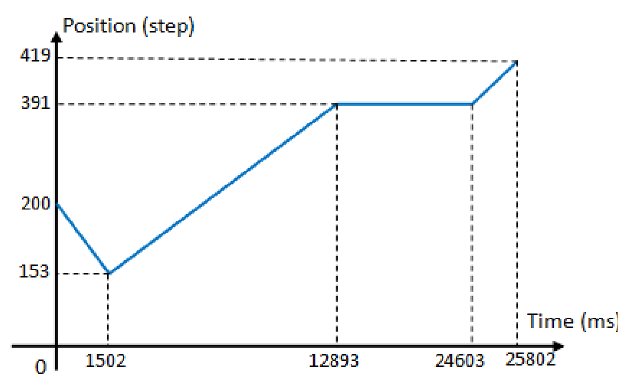

Fig. 3. Fictif movement of the recline for database construction

From this fictive movements, Table I presents the raw data, where multiple instances are characterized according to 5 attributes (Time, Action, the current I, the Position, the Velocity). Note that 'Action = 1' corresponds to the elevation of the recline, 'Action = 2' to the depression and 'Action = 0' is a steady position. Moreover, the position is measured in 'steps' of the potentiometer. This means that 'Step =0' corresponds to $\theta = 0$ and 'Step = 500' to $\theta = pi/2$ rad. Finally, to enrich the database construction in the context of supervised classification (see e.g. [21, 22]), an expert labels each instance, for example 'Class N = Normal' and 'Class V = Vibration'.

TABLE I
RAW DATABASE

Time (ms)	Action	I (mA)	Position (step)	Velocity (rad/s)	Class
0	1	260	200	-0.2	N
300	1	261	189	-0.2	N
605	1	263	179	-0.2	N
890	1	259	171	-0.2	V
1207	1	260	162	-0.2	V
1502	1	262	153	-0.2	N
1790	2	288	158	0.07	N
...					
12295	2	295	374	0.07	N
12602	2	294	383	0.07	N
12893	2	289	391	0.07	N
13206	0	0	391	0	N
13501	0	0	391	0	N
13799	0	0	391	0	N
...					
24302	0	0	391	0	N
24603	0	0	391	0	N
...					

Then, the data are aggregated for each completed movement, according to the user's actions. For instance, from 0 to 1502 ms, the user acts on the button '1'. Thus the movement starts when the user press the button and ends when it is released. Table II shows the aggregated instances. In practice, it means that all instances are aggregated while the 'Action' attribute (from the user keypad) keep the same value. The 'Time' attribute is simply transformed into the 'Duration' attribute which is the duration of the completed movement. Moreover, the regularity of the movement is computed when a completed movement ends as described in [16]. Finally, if no faults have occurred, the class of the instance is said normal 'N'. Whereas, if a fault has occurred, then the class value of the aggregated instance takes the value of the fault, for example 'V' for a vibration fault.

The database being now constructed, we can move to the learning and testing phases.

B. Learning and testing phases

Once the database is constructed, it is divided in two parts: a training set and a test dataset. The training set is used during the learning phase which consists in using a set of known instances and then building a learning model to represent the functioning of the system. This learning model is then used to predict the class of the different instances in the dataset. It is important to notice that the test dataset has no role to build the learning model and that both the training data and the test dataset are representative samples of the underlying problem.

Because of the small number of data in the database, one has considered a stratified cross-validation in the classification process [21, 22]. It consists in dividing the database into 10 parts. Nine-tenths are used during the training phase to create the learning model. Then, the remaining one is used for testing the tenth part and to calculate the rate of classification error . This procedure is repeated 10 times on different training sets. Finally, the final value of the error rate is computed as the average of the 10 error rates previously calculated [21, 22].

Different classifiers, implemented on WEKA[1] software [21], have been used in this study in order to examine the database. This have been done without and with the proposed observer based estimation of the velocity for comparison purposes. The following classification algorithms have been considered:

- J48 which is the implementation of the decision table algorithm C4.5 [23]. It is used to generate decision trees that can be used for classification. The decision trees consist in checking for base cases, calculating the gain ratio for each attribute and choosing the one that has the highest normalized information gain, then creating a decision node that splits the database and doing the same thing for the children of nodes.
- Multilayer Perceptron [24]. It is an artificial neural network model for nonlinear classification [21], which computes a single output from input data by forming a combination based on input weights.
- PART [25] is a classification rules algorithm using "covering" approach that consists in identifying, at each stage, a rule that covers some of the instances.
- BayesNet [26] is a Bayesian network that produces probability estimations rather than hard classifications. It consists in estimating the probabilities that a given instance belongs to each class value.

The choice of the classifier to be further embedded in a commercial version of the seat can be made on the highest accuracy rates throughout the classification tests of the constructed database. The accuracy rate being the proportion of instances correctly classified. The results, obtained from experimental measurements, are detailed in the next section.

V. EXPERIMENTAL RESULTS

In order to validate the proposed FDD approach, multiple series of experiments have been realized on WEKA by using the aggregated database without and with estimated attributes. For this experimental validation, with the experimental measurements and estimated ones, a database has been constructed with 114 labelled instances. The labelling by the expert revealed 5 types of classes: N 'Normal'; I 'Irregular'; O 'Overconsumption'; S 'Mechanical sliding' and B 'Mechanical blockade'. To illustrate this point, Fig. 4 shows for the recline in action a sample of measured data (angular position and current consumption) and estimated ones (angular velocity). In this sample, one can distinguished two sequences (a) and (b). In the sequence (a), a current over-consumption occurred during a rising movement of the recline. In the sequence (b) a normal current consumption occurred during a rising movement. This figure shows also the estimated velocities obtained from the linear observer proposed in [16] and the above designed T-S observer. As shown by the plot of the

[1] http://www.cs.waikato.ac.nz/ml/weka/

TABLE II
AGGREGATED DATABASE

N^o	Duration (ms)	Action Action	I (mA)	Displacement (steps)	Velocity (rad/s)	Regularity	Class
1	1502	1	261	-47	-0.2	0.8	V
2	11391	2	291.5	238	0.07	0.99	N
3	11710	0	0	0	0	1	N
...							

velocity estimation errors, the T-S observer perfectly match the recline velocity while significant velocity errors occurre for the linear observer.

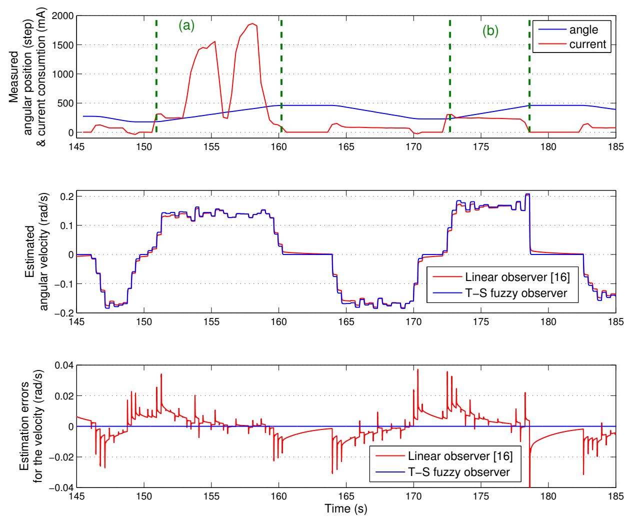

Fig. 4. Sample of measured and estimated data (measured position and current, estimated velocities)

The experimental results of the proposed FDD approach on the actuated seat are presented in Table III. These results are given for the 4 classifiers that have been detailed above.

One can notice that the accuracy rate of classification has been improved with 2 methods (J48 and BayesNet) when the velocity estimated by the linear observer design in [16] has been considered as attribute. Moreover, when the T-S observer-based estimations are considered, the accuracy rate of classification has been significantly improved with all the considered classification algorithms. For example, when observer-based estimations are considered, the maximum improvement is reached by J48. It is about 1.7544 % and 2.6315 % respectively with the linear and the T-S observer-based estimations.

These results show that the best accuracy classification rate is obtained when the T-S observer-based estimations are considered as attribute for the classification process. In other words, faults are better detected with the T-S observer-based estimation than without it. This confirm the effectiveness of the proposed approach, which merges T-S observer-based estimation and data-driven classification for the FDD of the considered actuated seat.

VI. CONCLUSION

An improved FDD approach, mixing observer-based estimations and supervised classification algorithms, for an actuated seat has been proposed in this paper. It consists in merging measured data from a real system and estimated data from a fuzzy T-S state observer in order to enrich the classification database. The latter is then considered in supervised classification algorithms to perform the FDD process. It has been shown from experimental reasults that the proposed observer-based estimations improve the accuracy rate of the classification process, and so the FDD results.

Further works will be done to design an unknown input observer in order to remove torques estimations and/or measurements for the commercial version of the seat. In addition sequential database will be considered for the classification purpose in order to reduce the embedded computational cost. Moreover, to improve the scalability of the proposed approach, robust observer design based on an uncertain nonlinear model of the seat will be further considered in order to cope with the users' weights variability. These further developments constitute our works in progress.

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TABLE III
CLASSIFICATION RESULTS OF THE AGGREGATED DATABASE

	Without estimation	With linear observer-based estimation [16]	With the proposed T-S observer-based estimation
Classifier	Accuracy rate (%)	Accuracy rate (%)	Accuracy rate (%)
J48	91.2281	92.9825	93.8596
Multilayer perceptron	92.1053	91.2281	92.9825
PART	91.2281	89.4737	92.1053
BayesNet	91.2281	92.1053	92.9825

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