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► **To cite this version:**

Mathias Blandeau, Thierry-Marie Guerra, Víctor Estrada Manzo, Philippe Pudlo, François Gabrielli. Unknown input observer based on discrete-time nonlinear descriptor model for understanding sitting control. 20th World Congress of the International Federation of Automatic Control, Jul 2017, Toulouse, France. pp. 820-825, 10.1016/j.ifacol.2017.08.146 . hal-03413110

**HAL Id: hal-03413110**

**<https://uphf.hal.science/hal-03413110v1>**

Submitted on 22 Sep 2023

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# Unknown input observer based on discrete-time nonlinear descriptor model for understanding sitting control

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**Abstract:** The present paper studies sitting control for persons with complete thoracic spinal cord injury by means of automatic control. The methodology begins by modeling sitting control, after a discretization of the nonlinear descriptor model is computed, then a Takagi-Sugeno model is obtained for further manipulations. The approach uses unknown input observers to estimate states and internal variable of the system. The design conditions are expressed as linear matrix inequalities, whose solvability depends on convex optimization techniques. Simulations are conducted to show the effectiveness of the proposed observer.

**Keywords:** Unknown input observer, Takagi-Sugeno models, Inverted pendulum, Spinal Cord Injury, Sitting movement, Nonlinear descriptor systems, Discrete-Time systems.

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## 1. INTRODUCTION

Sitting control is the aptitude to maintain one's stability in seated position when exposed to perturbations. It is one of the most crucial goals of rehabilitation after suffering a complete spinal cord injury (SCI) (Janssen-Potten et al., 2001), mainly because the muscle contractions in the lumbar and abdominal region are reduced or worst impossible. Despite its importance in the everyday life of people living with SCI, sitting control is still little-known (Vette et al., 2010). The human anatomical complexity impels us to consider various mechanical actions to sitting control (active joint force, passive joint resistance, etc. (Panjabi, 1992)), thus we need to use a mathematical model to represent all these contributions and observe experimentally their impact on sitting stability.

The biomechanical modelling of human body naturally leads to nonlinear systems in descriptor form (Blandeau et al., 2016; Guelton et al., 2008) with the property of the inertia matrix being invertible. An exact convex representation of an original nonlinear system can be computed by means of the sector nonlinearity approach (Ohtake et al., 2001), producing a Takagi-Sugeno (TS) descriptor model (Taniguchi et al., 1999). This methodology has proven to be effective when combined with the direct Lyapunov method, since the stability/design conditions, normally, yield in terms of linear matrix inequalities (LMIs), whose solvability can be easily determine via convex optimization techniques (Boyd et al., 1994). Recent approaches for discrete-time TS descriptor systems have relaxed results in comparison with standard representations (Estrada-Manzo et al., 2016, 2015).

On the other hand, unknown input observers (UIO) in TS descriptor form have been firstly used in biomechanics (Guelton et al., 2008); latter, for the study of sitting control with the introduction of a variation of the double inverted pendulum (Blandeau et al., 2016). These approaches have been developed for continuous time models. Several drawbacks appeared, including the treatment of the input delay and the difficulty to cope with the angular speed as an unmeasured premise. This last issue is still an open problem for TS observers (Ichalal et al., 2012). Another possibility, exploited in this paper, is to use the discrete time framework. Therefore, the main goal of the paper consists in the design of a discrete-time TS-UIO to estimate internal variables like generated forces. Of course, the goal will be to reduce the previous drawbacks of the continuous time case especially concerning unmeasured premise variables; therefore the proposed UIO allows us to estimate non-measured values of the states and also the input of the model from the measured output during simulations or experimentations.

This paper is organized as follows: Section 2 presents the discretization for the continuous descriptor model as well as its convex model; Section 3 explains the main results to derive an UIO for estimating the stabilization force; Section 4 provides the simulation results for the proposed approach; Section 5 discusses the obtained results and future works; and Section 6 concludes the paper.

## 2. THE H2AT MODEL

### 2.1 Modeling from continuous-time to discrete-time:

The H2AT model has been introduced in previous works (Blandeau et al., 2016). H2AT stands for “head, two arms and trunk” and introduces a new way to model sitting control by taking into account the action of upper segments in the stabilization process (an scheme is given in Figure 1). In the continuous case, the dynamical model is:

$$\begin{cases} m_1\ddot{x} - m_1l_0\ddot{\theta} = m_1x\dot{\theta}^2 - m_1g \sin(\theta) + F(t - \tau) \\ -m_1l_0\ddot{x} + J(x)\ddot{\theta} = -2m_1x\dot{x}\dot{\theta} + (m_1l_0 + m_2l_c)g \sin(\theta) \\ \qquad \qquad \qquad -m_1xg \cos(\theta), \end{cases} \quad (1)$$

where  $J(x) = m_1l_0^2 + m_1x^2 + m_2l_c^2$ . A natural state space representation of (1) with a state vector  $X(t) = [x(t) \ \dot{x}(t) \ \theta(t) \ \dot{\theta}(t)]^T$  yields

$$\begin{aligned} E(X(t))\dot{X}(t) &= A(X(t))X(t) + BF(t - \tau) \\ y(t) &= CX(t), \end{aligned} \quad (2)$$

where  $X(t) \in \mathbb{R}^n$  is the state of the system,  $y(t) \in \mathbb{R}^o$  is the output of the system, and  $F(t - \tau) \in \mathbb{R}^d$  is the unknown input. The matrices are defined as follows

$$E(X) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & m_1 & 0 & -m_1l_0 \\ 0 & 0 & 1 & 0 \\ 0 & -m_1l_0 & 0 & J(X) \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \quad C = \begin{bmatrix} 0 & 1 \\ 0 & 0 \\ 1 & 0 \\ 0 & 0 \end{bmatrix}^T, \text{ and}$$

$$A(X) = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & -m_1g \frac{\sin(\theta)}{\theta} & m_1x\dot{\theta} \\ 0 & 0 & 0 & 1 \\ -m_1g \cos(\theta) & -2m_1x\dot{\theta} & (m_1l_0 + m_2l_c)g \frac{\sin(\theta)}{\theta} & 0 \end{bmatrix}$$

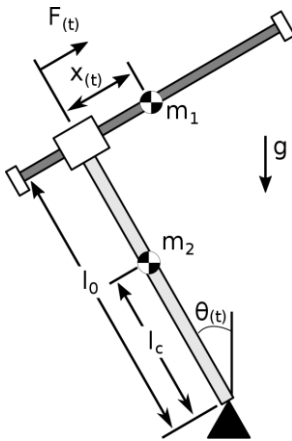


Fig. 1. H2AT Pendulum

Note that (2) is a descriptor system whose matrix  $E(X)$  is always invertible and positive definite.

In order to express (2) in discrete-time, we introduce the following discrete state vector  $X_d(k) = [x_k \ \dot{x}_k \ \theta_k \ \dot{\theta}_k]^T$ , and using classical the Euler's approximation, the following system is obtained:

$$E(X)X_d^+ = A_d(X)X_d + sBF(k - \tau), \quad y_k = CX_d \quad (3)$$

with  $A_d(X) = sA(X) + E(X)$  in the form:

$$A_d(X) = \begin{bmatrix} 1 & s & 0 & 0 \\ 0 & m_1 & -sm_1g \frac{\sin(\theta)}{\theta} & sm_1x\dot{\theta} - m_1l_0 \\ 0 & 0 & 1 & s \\ -sm_1g \cos(\theta) & \begin{pmatrix} -2sm_1x\dot{\theta} \\ -m_1l_0 \end{pmatrix} & \begin{pmatrix} s(m_1l_0 + m_2l_c) \\ \times g \frac{\sin(\theta)}{\theta} \end{pmatrix} & J(x) \end{bmatrix}$$

**Remark 1.** The nonlinear model (2) is inherently unstable. It needs to be controlled before performing any estimation. A robust approach is employed on control of input delayed models of the form (Yue and Han, 2005):

$$u(t) = L \left[ X(t) + \int_{t-\tau_0}^t e^{A(t-s-\tau_0)} Bu(s) ds \right]. \quad (4)$$

Both the issues of LMI constraints and control law implementation have been discussed in (Blandeau et al., 2016).

### 2.2 Convex modeling: exact Takagi-Sugeno systems

The sector nonlinearity methodology is applied on the discrete-time nonlinear descriptor model (3), as a result an equivalent TS descriptor model form (Taniguchi et al., 1999) is obtained:

$$E_h X_d^+(k) = A_{dh} X_d(k) + Bd(k), \quad (5)$$

with  $E_h = \sum_{i=1}^r h_i(k)E_i$  and  $A_{dh} = \sum_{i=1}^r h_i(k)A_{di}$  are convex sums of matrices coming from the sector nonlinearity methodology,  $d(k)$  is considered as an unknown input that has to be estimated. Anatomical constraints lead us to consider the following compact set

$$\Omega_x = \left\{ \begin{array}{l} -0.075 \leq x \leq 0.105 \text{ (meters)} \\ x, \theta, \dot{\theta}: -0.087 \leq \theta \leq 0.122 \text{ (rad)} \\ |\dot{\theta}| \leq 0.209 \text{ (rad/s)} \end{array} \right\} \quad (6)$$

Four nonlinear terms can be identified in (3) as well as their bounds, they can be grouped in the premise variable vector  $z \in \mathbb{R}^4$ :

$$\begin{aligned} z_1 &= \sin(\theta_k) / \theta_k \in [0.9975, 1] & z_2 &= \cos(\theta_k) \in [0.9926, 1] \\ z_3 &= x_k \dot{\theta}_k \in [-0.0220, 0.0220] & z_4 &= x_k^2 \in [0, 0.0111] \end{aligned}$$

Now, the membership functions (MFs) can be constructed with the following weighting functions (WFs):

$$w_0^j(\cdot) = \frac{z_j(\cdot) - \underline{z}_j}{\bar{z}_j - \underline{z}_j}, \quad w_1^j(\cdot) = 1 - w_0^j(\cdot), \quad j \in \{1, 2, 3, 4\}, \quad (7)$$

where  $\underline{z}_j$  and  $\bar{z}_j$  are the minimum and the maximum of their corresponding premise variable. The MFs are defined according to the following notation:

$$h_i = h_{d_1^i \times 2^{p-1} + \dots + d_3^i \times 2 + d_4^i + 1} = \prod_{j=1}^4 w_{d_j^i}^j(z_j), \quad (8)$$

where  $i = d_1^i \times 2^{p-1} + \dots + d_3^i \times 2 + d_4^i + 1 \in \{1, \dots, 2^4\}$  is the number of rules (16 therein),  $k \in \{1, \dots, 4\}$  and  $d_k^i \in \{0, 1\}$  is the  $k^{\text{th}}$  digit of the  $p$ -digit representation of  $i-1$ . For example  $h_{10} = w_1^1 \times w_0^2 \times w_0^3 \times w_1^4$  and the corresponding matrices are:

$$(E_{10}, A_{d10}) = (E(z_4), A_d(z_4, \bar{z}_2, \bar{z}_3, \underline{z}_4)).$$

Note that the MFs hold the convex sum property in  $\Omega_X$ :

$$\sum_{i=1}^{16} h_i(z) = 1, \quad 0 \leq h_i(z) \leq 1.$$

The resulting TS descriptor model (5) is an *exact* representation of the nonlinear one (3).

Now, to capture the dynamic of the discrete-time unknown input  $d(k)$ , a 2<sup>nd</sup> order discrete integrator is used

$(z-1)^{p+1} d(k) \approx 0$  with  $p=1$ . This choice has been made after some real data trials and is a good compromise between accuracy of the results and complexity of the observer, especially in terms of gains and order. Thus, its dynamics writes:

$$D^+ = \Gamma \times D \Leftrightarrow \begin{bmatrix} d^+ \\ d^{++} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -1 & 2 \end{bmatrix} \begin{bmatrix} d \\ d^+ \end{bmatrix}, \quad (9)$$

with  $D \in \mathbb{R}^{2d}$ . Thus (5) and (9) yields the following extended system

$$E_h^e(x_k) X^{e+} = A_h^e(x_k, \theta_k, \dot{\theta}_k) X^e, \quad y_k = C^e X^e, \quad (10)$$

with the extended vector  $X^e = \begin{bmatrix} X_d \\ D \end{bmatrix} \in \mathbb{R}^{n+\bar{n}}$ ,

$$E_h^e = \begin{bmatrix} E_h & 0 \\ 0 & I_2 \end{bmatrix}, \quad A_h^e = \begin{bmatrix} A_{dh} & sB & 0 \\ 0 & \Gamma & \end{bmatrix}, \quad \text{and} \quad C^e = [C \ 0].$$

Obviously  $E_h^e$  is still regular for all  $X \in \Omega_X$ .

### 2.3 Non-measured premise variable

For the continuous time model (2) the unmeasurable premise comes from the terms in  $A(X)$  depending on the angular

speed  $\dot{\theta}(t)$ . For its discretization (3) and for the TS descriptor model (5)  $\dot{\theta}_k$  appears in  $A_d$  and concerns the premise variable  $z_3$ .

The general issue of unmeasured premise variables is still an open problem. Recent techniques using immersion approach have been proposed to cope with them (Ichalal et al., 2016). Nevertheless, its application in our case seems very difficult due to the nature of the nonlinear model. A simpler way to deal with it has been to consider that, for a sufficiently small time sample, the approximation of  $\dot{\theta}_k$  by  $\dot{\theta}_{k-1}$  can be used. This assumption has been validated through the results.

### 2.4 Simulation protocol

In order to get closer to the real-time protocol, which is the next step of the study, the following simulation is considered through this work. A generalized stabilized model is considered including the continuous H2AT model (1) and its stabilization via control law (4) considering a delay  $\tau$ . This generalized model is a “black box” from which the only measurements are  $[x(t) \ \theta(t)]$  and the unknown input observer has to reconstruct the unknown input  $F(t-\tau)$  drawn with a “?” on Figure 2. The assumption made in section 2.3 means that the internal calculus of the fuzzy descriptor observer uses  $\dot{\theta}_{k-1}$  instead of  $\dot{\theta}_k$  for  $A_d$ . Of course, the simulation process can validate the entire procedure as we can exhibit the error  $F(t-\tau) - \hat{F}(t-\tau)$ .

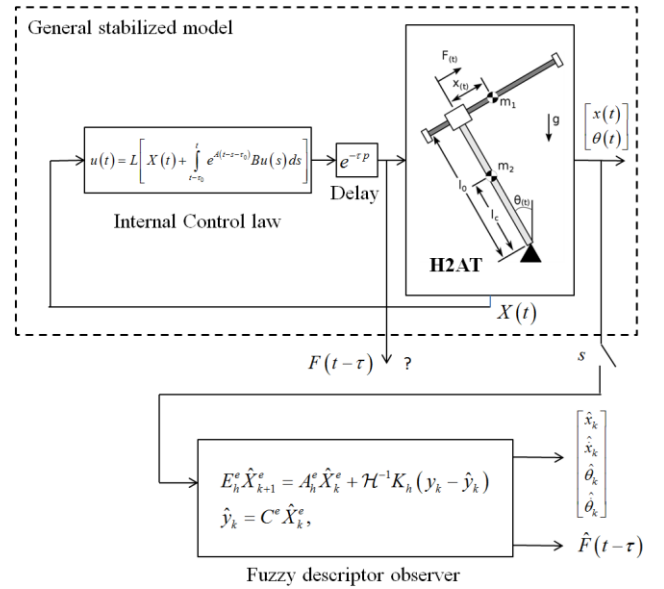


Fig. 2 Simulation structure

## 3. MAIN RESULT

For the UIO design the discrete-time TS descriptor system (10) is employed. Therefore, following ideas in (Estrada-Manzo et al., 2016), the following observer is defined:

$$E_h^e \hat{X}_{k+1}^e = A_h^e \hat{X}_k^e + \mathcal{H}^{-1} K_h (y_k - \hat{y}_k), \quad \hat{y}_k = C^e \hat{X}_k^e, \quad (11)$$

#### 4. SIMULATION RESULTS

with  $\hat{X}^e = \begin{bmatrix} \hat{X}_d \\ \hat{D} \end{bmatrix}$  as the extended estimation vector. Matrices

$\mathcal{H} \in \mathbb{R}^{(n+2d) \times (n+2d)}$  and  $K_h \in \mathbb{R}^{(n+2d) \times o}$  are nonlinear gains to be designed via LMIs. To this end, let us define an estimation error  $e_k = X_k^e - \hat{X}_k^e$ , and its dynamics as:

$$E_h^e e_{k+1} = (A_h^e - \mathcal{H}^{-1} K_h C^e) e_k. \quad (12)$$

Let us consider the following generic Lyapunov function candidate:

$$V(e_k) = e_k^T \mathcal{P} e_k, \quad \mathcal{P} = \mathcal{P}^T > 0. \quad (13)$$

The following result establishes the LMI design for (11).

**Theorem 1.** The origin of the error dynamics (12) is asymptotically stable if there exists  $P = P^T > 0$ ,  $H \in \mathbb{R}^{(n+2d) \times (n+2d)}$ , and  $K_j \in \mathbb{R}^{(n+2d) \times o}$ ,  $j \in \{1, 2, \dots, 16\}$  such that the following inequality holds:

$$\begin{bmatrix} -P & (HA_i^e - K_i C^e)^T \\ HA_i^e - K_i C^e & P - HE_i^e - (HE_i^e)^T \end{bmatrix} < 0, \quad i \in \{1, 2, \dots, 16\}. \quad (14)$$

*Proof:* Rewrite the error dynamics (12) as:

$$\begin{bmatrix} A_h^e - \mathcal{H}^{-1} K_h C^e & -E_h^e \end{bmatrix} \begin{bmatrix} e_k \\ e_{k+1} \end{bmatrix} = 0 \quad (15)$$

Similar for the difference of the Lyapunov function (13)

$$\Delta V(e_k) = \begin{bmatrix} e_k \\ e_{k+1} \end{bmatrix}^T \begin{bmatrix} -\mathcal{P} & 0 \\ 0 & \mathcal{P}^+ \end{bmatrix} \begin{bmatrix} e_k \\ e_{k+1} \end{bmatrix} < 0. \quad (16)$$

Then, by Finsler's Lemma (16) holds under equality constraint (15) if:

$$\begin{bmatrix} 0 \\ \mathcal{H} \end{bmatrix} \begin{bmatrix} A_h^e - \mathcal{H}^{-1} K_h C^e & -E_h^e \end{bmatrix} + (*) + \begin{bmatrix} -\mathcal{P} & 0 \\ 0 & \mathcal{P}^+ \end{bmatrix} < 0. \quad (17)$$

Chose  $\mathcal{P} = P$  and  $\mathcal{H} = H$ , then the desired result (14) is obtained.  $\square$

**Remark 2.** The given LMI conditions in Theorem 1 can be improved by changing the  $\mathcal{P}$  and  $\mathcal{H}$  for nonlinear ones. For instance:  $\mathcal{P} = P_h = \sum_{j=1}^{16} h_j(z) P_j$  leads to a non-quadratic Lyapunov function (Guerra and Vermeiren, 2004).

**Remark 3.** As expected, different performances can be directly added to the LMI problem in Theorem 1. For instance, a decay rate  $\beta$  (speed convergence) yields:

min  $\beta$  subject to

$$\begin{bmatrix} -\beta P & (HA_i^e - K_i C^e)^T \\ HA_i^e - K_i C^e & P - HE_i^e - (HE_i^e)^T \end{bmatrix} < 0, \quad i \in \{1, 2, \dots, 16\}.$$

for  $0 < \beta < 1$ .

The simulation results are presented in this section. The nonlinear model (2) was simulated under the control law (4) with  $L = [8126 \ 1629 \ -6954 \ -1346]$  and using as input delay  $\tau_0 = 60ms$ . The sampled output values were fed to the discrete-time observer (11) in order to estimate both the state vector and the unknown input  $d(k)$ . The initial conditions are  $X_d(0) = [0 \ 0 \ 0.005 \ 0]^T$  and  $\hat{X}_d(0) = 0_{4 \times 1}$ . The sampling period chosen is  $s = 0.01sec$  and the decay rate performance of  $\beta = 0.2$  (see Remark 3). Some of the matrices solution of the LMI constraints problem are given:

$$P = \begin{bmatrix} 9.6e+4 & * & * & * & * & * \\ -1.1e+3 & 15.0 & * & * & * & * \\ 6.7e+3 & 38.4 & 4.3e+4 & * & * & * \\ 12.1 & -1.2 & -4.4e+2 & 5.2 & * & * \\ 4.0 & -0.06 & 1.20 & -0.02 & 5e-4 & * \\ -2.1 & 0.04 & -0.48 & 7.8e-3 & -3e-4 & 2e-4 \end{bmatrix}$$

$$H = \begin{bmatrix} 5.2e+4 & * & * & * & * & * \\ -679 & 1.2 & * & * & * & * \\ 1.8e+4 & -82.3 & 2.8e+4 & * & * & * \\ -107.4 & 0.94 & -308.0 & 1.9 & * & * \\ 3.20 & -0.01 & 0.49 & -0.02 & 5e-4 & * \\ -1.67 & 0.07 & -0.17 & 0.01 & -3e-4 & 2e-4 \end{bmatrix}$$

The first step is to show that the assumption made in section 2.3, i.e. the approximation of  $\dot{\theta}_k$  by  $\dot{\theta}_{k-1}$  is fruitful. Figure 3 presents the difference on the unknown input estimation between two observers: the first one where  $\dot{\theta}_k$  is supposed known and it represents the "ideal-impossible" observer result, the second where the approximation  $\dot{\theta}_{k-1}$  is used. The figure shows clearly the validity of the approximation.

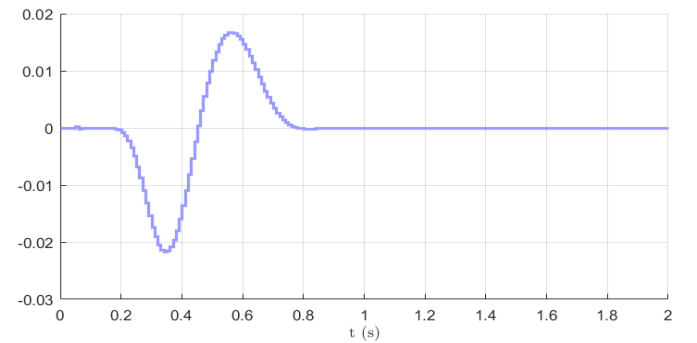


Fig. 3 Error (in %) due to assumption in section 2.3

On Figure 4 we can see the result of this simulation with the continuous states in blue and the discrete-time estimations in black. The observer manages to estimate the different states and follow their dynamic after 0.1s.

Then the unknown input was reconstructed and the estimation error was computed (see Figures 5 and 6). The unknown input was well estimated with less than 5% error after 0.4s. To exhibit the behavior of the observer towards disturbance, a sinusoidal disturbance was added to  $\theta(k)$  from 0 to 6.3 seconds. Figure 7 shows the observer reconstruction of the unknown input during the whole simulation.

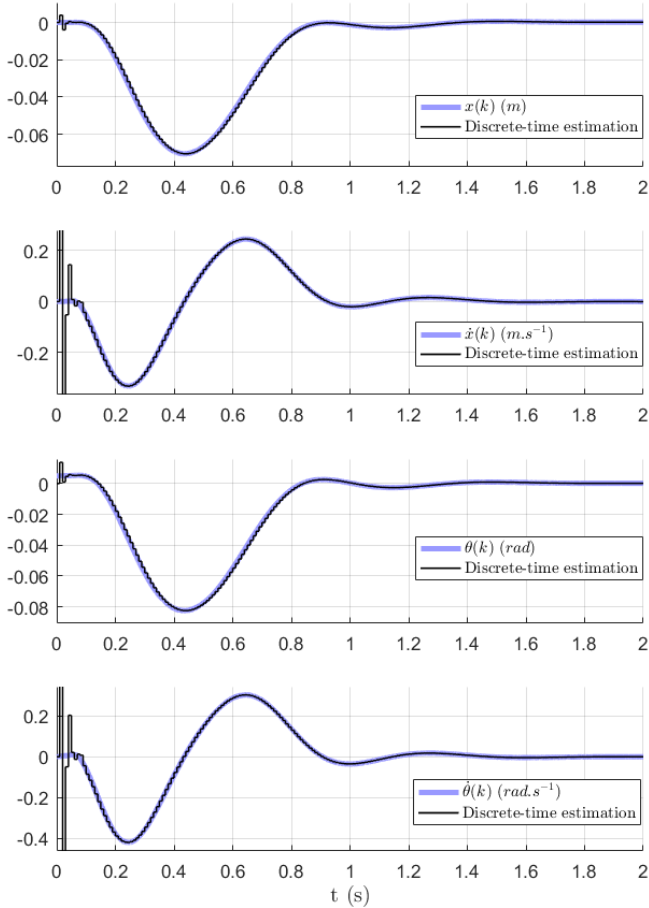


Fig. 4. State discrete-time estimation

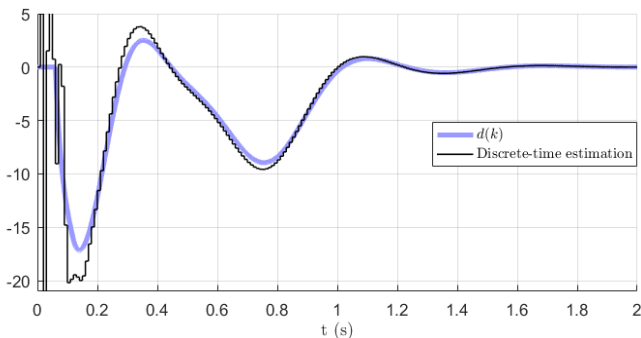


Fig. 5. Unknown input discrete-time estimation

The spikes at the first samples of the simulation are due to initial conditions problems that will not occur for real time experiments. The whole scheme, Figure 2, requires to take into account the delay in the control, therefore the beginning of the trials imply a sequence where during  $\tau$  seconds no activity is seen from the observer. Voluntarily, this effect was kept in the figures to show the capability of the observer, even in this “worse” case to converge.

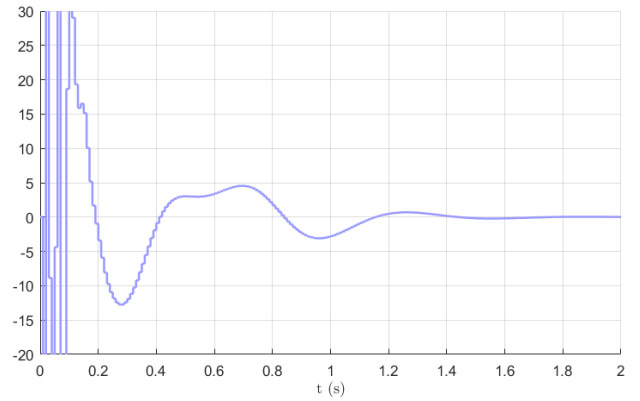


Fig. 6. Unknown input estimation error (in %)

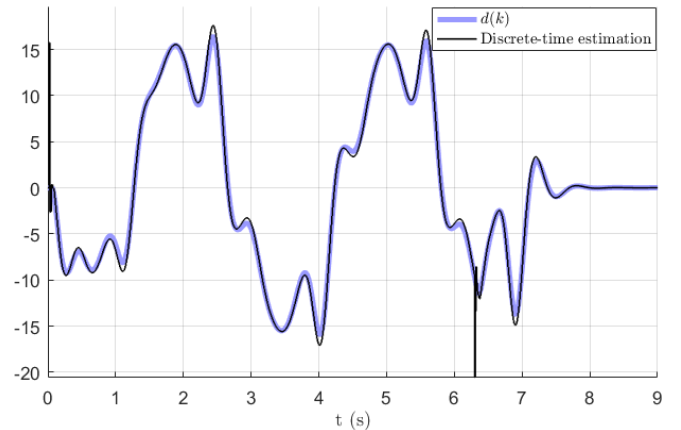


Fig. 7. Unknown input estimation with disturbance

## 5. DISCUSSION

The main goal of this paper is to study sitting control for people living with SCI. The equations of the already existing H2AT model were discretized in order to be fitted to the use of experimental data and an unknown input observer in descriptor form was designed. The recent work of (Estrada-Manzo et al., 2014) was used to express the observer convergence in the form of LMI conditions.

The observation results in simulation shows the ability to quickly converge despite the presence of disturbance. Regardless of the assumption made to cope with the non-measured premise, the UIO estimates the states and the unknown input correctly, that proves one of the interests of handling the problem via a discrete form observer.

The H2AT model represents one’s aptitude to maintain a seated position by moving back and forth the upper limbs and the head. Although this movement can be seen during rehabilitation training, some geometrical and mechanical hypotheses were made in the creation of the model. First of all, a geometrical validation of the model with experimental data must be made to confirm if subjects moves their arms perpendicularly to the trunk and as the same height as their shoulder. Second, we consider no resistance in the lumbar joint, this kind of assumption has been made in biomechanical modelling of standing and sitting posture (Peterka, 2000; Vette et al., 2010) and it is correct when considering voluntary muscle activity for SCI people.

Nonetheless, the presence of resistive forces generated by passive physiological action after trunk flexion and extension has been described (Cholewicki et al., 1999; Panjabi, 1992). These observation needs to be taken into account in order to improve our modelling of sitting control and thus our estimation results.

## 6. CONCLUSIONS

We wish to emphasize the method of the UIO as another way to estimates unmeasurable values in biomechanics. Futures research are directed to experimental validation of the observer, geometrical adaptation of the model and increasing the complexity of the model in order to take into account passive resistance.

## ACKNOWLEDGEMENTS

This work is supported by the French Ministry of Higher Education and Research, the National Center for Scientific Research (CNRS), the Nord-Pas-de-Calais Region, ITSON-PROFAPI project No. 2016\_0091, Zodiac Seat France and Direction Générale de l'Aviation Civile (project n°2014 930181). The authors gratefully acknowledge the support of these institutions.

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