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Fuzzy unknown input observer for understanding sitting control of persons living with spinal cord injury

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ABSTRACT

The present paper introduces a simple model to study sitting control for persons with complete thoracic spinal cord injury. The system is obtained via Lagrangian techniques; this procedure leads to a nonlinear descriptor form, which can be written as a Takagi–Sugeno model. A first attempt to estimate the sitting control in disabled people is done via an unknown input observer. The conditions are expressed as linear matrix inequalities, which can be efficiently solved. Simulation results validate the proposed methodology as the observations are coherent with and without perturbations.

1. Introduction

People living with a complete spinal cord injury (SCI) lose all sensibility and mobility below their injury level. An injury in the lumbar region would result in the loss of the lower limbs and any higher injury will affect the abdominal belt, the back and intervertebral muscles which are required to finely adjust the inherently unstable human spine (Crisco et al., 1992; Silfies et al., 2003) or stabilize it in the presence of perturbation. In the absence of those muscles, people living with SCI can use instead their upper limbs and head as a compensatory strategy to maintain equilibrium (Grangeon et al., 2012) as they are trained in rehabilitation (Janssen-Potten et al., 2001).

The majority of existing models for the study of sitting stability are linked-segment model allowing simple mechanical representation of the anatomical complexity of the body with active and passive contributions (Panjabi, 1992), nevertheless the representation are often inappropriate for the application to the SCI sitting stability because the trunk and arms are considered rigid (Cholewicki et al., 1999; Vette et al., 2010) or because the muscular activity is concentrated at the lumbar joint (Reeves et al., 2009; Tanaka and Granata, 2007). The H2AT model (for "head, two arms and trunk"), a variation of the inverted pendulum, taking into account the action of the upper limbs and head has been proposed for this specific topic (Blandeau et al., 2016a).

Modeling mechanical systems leads to non-linear descriptor with an invertible inertia matrix (Lewis et al., 2003) which can be exactly represented by Takagi–Sugeno (TS) model via the sector nonlinearity approach (Ohtake et al., 2001; Taniguchi et al., 1999). This approach has been adapted to biomechanical systems (Guelton et al., 2008) combined with direct Lyapunov method to develop an unknown input observer (UIO) for the estimation of unmeasured variables and inputs but, the convergence conditions were expressed in terms of bilinear matrix inequalities (BMI), which are difficult to solve. Recently Guerra et al. (2015) solved this problem and obtained a linear matrix inequality (LMI) constraints problem (Boyd et al., 1994). This methodology is adopted in the current paper; its objective is to understand the way an individual with complete thoracic SCI maintains its equilibrium by estimating internal variables of force generation via UIO and TS descriptor models. Moreover the H2AT model in its TS form presents the well-known problem of non-measurable premise variables. This problem, in its general form is still one open problem of the TS modeling (Ichalal et al., 2016). This problem has been solved in our particular case using a robust-like control approach for the convergence of the state error estimation. Thus, the main interest is to guarantee the convergence of the general observer including the non measured premise variable without extra assumptions such that Lipschitz conditions that are generally used.

As people living with SCI, the H2AT is unstable in open-loop, the first step is then to derive an "internal" control law, compatible with the human behavior, to get a stable closed-loop system. Because all human action are delayed, from sensing a perturbation to muscle activation

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(Reeves et al., 2007), the design of the control law is based on a time-varying input control law from Yue and Han (2005) adapted to the descriptor form. A problem of implementation also appears as the control law is delay-distributed. This problem has been solved using a nonlinear dynamic extension to end with a dynamic feedback control law.

This paper is organized as follows: Section 2 presents the modeling of H2AT via Lagrangian techniques, the design and implementation of the control law and the TS modeling; Section 3 explains the way to derive a UIO for the states and input observation, Section 4 provides the simulation results and discusses the obtained results and Section 5 concludes the paper and gives future works.

2. Problem statement

The H2AT model has been introduced in previous works (Blandeau et al., 2016a). 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 (upper limbs and head) in the stabilization process.

2.1. Modeling

The H2AT pendulum is an extended version of the planar inverted pendulum consisting of two rods. The first one represents the trunk as a classical inverted pendulum while the second rod represents the head and arms slides at the top of the first one. The controlling force $F(t)$ will make the upper rod slide on the lower one. Fig. 1 shows the H2AT system scheme.

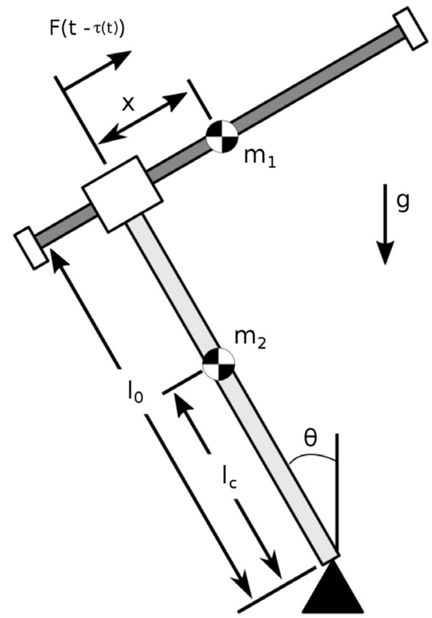

Fig. 1. H2AT pendulum.

This model is generic and just requires a minimum of biomechanical parameters. For the simulations, we consider a 80 kg male subject. As arms and trunk mass do not change between control subject and SCI subject (Jones et al., 2003), we can use regression rules to get segment mass and length (Dumas et al., 2007): $m_1 = 16.1$ kg stands for the mass of the upper segment, corresponding to the head, neck, and arms; $m_2 = 26.64$ kg is the mass of the trunk; $l_0 = 477$ mm is the length of the trunk; and $l_c = 276.66$ mm is the length of the center of mass of the trunk. A full neck flexion with both arms stretched gives a value of $x = 105.27$ mm whereas an extension of the neck and arms gives $x = -75.18$ mm (Kapandji, 2005). The resulting compact set is $\Omega_x = \begin{Bmatrix} -0.075 \leq x \leq 0.105 \\ -0.175 \leq \theta \leq 0.349 \\ -0.5 \leq \dot{\theta} \leq 0.5 \end{Bmatrix}$ in meters, radians and rad/s.

To obtain the dynamic equations of the system, we calculate its Lagrangian $L = K - U$ where K, U are the kinetic and potential energies of the system, respectively. Thus, consider $K = K_1 + K_2$ with $K_1 = \frac{m_1}{2}\left(l_0^2\dot{\theta}^2 + \dot{x}^2 + x^2\dot{\theta}^2 - 2l_0\dot{x}\dot{\theta}\right)$, $K_2 = \frac{1}{2}m_2 l_C \dot{\theta}^2$; and $U = U_1 + U_2$ with $U_1 = m_1 g\left(l_0\cos(\theta) + x\sin(\theta)\right)$, $U_2 = m_2 g l_c \cos(\theta)$.

Hence, by considering

$$\frac{d}{dt}\frac{\partial L}{\partial \dot{x}} - \frac{\partial L}{\partial x} = F(t-\tau(t)) \quad \text{and} \quad \frac{d}{dt}\frac{\partial L}{\partial \dot{\theta}} - \frac{\partial L}{\partial \theta} = 0,$$

we obtain

$$\begin{aligned} 0 &= m_1\ddot{x}_l(t) - m_1 l_0\ddot{\theta}(t) - m_1 x_l(t)\dot{\theta}^2(t) + m_1 g\sin(\theta(t)) - F(t-\tau(t)) \\ 0 &= -m_1 l_0\ddot{x}_l(t) + J\left(x_l(t)\right)\ddot{\theta}(t) + 2m_1 x_l(t)\dot{x}_l(t)\dot{\theta}(t) \\ &\quad - \left(m_1 l_0 + m_2 l_c\right) g\sin(\theta(t)) + m_1 g x_l(t)\cos(\theta(t)), \end{aligned} \tag{1}$$

where $J\left(x_l(t)\right) = m_1\left(l_0^2 + x_l^2(t)\right) + m_2 l_c^2$. The input includes a time-varying delay $\tau(t)$ due to neural transmission and the muscle force generation and is varying according to the individual; a classical range is for example 60 ms ± 10 ms. Of course, due to the absence of control of the trunk and intervertebral muscles, the model exhibits unstable open-loop behavior, as shown for example, in Fig. 2, using the H2AT initial parameters at $t = 0$ s: $\theta = -0.175$ rad, $x = 0$ mm, and $F = 100$ N. Because of the gravity effect, the trunk should have continued in negative values but with x increasing fast, the trunk rotates in the opposite direction and ends up falling down.

The goal of this study is to estimate the delayed input $F(t-\tau(t))$. To this end, system (1) is rewritten in a state–space form using the following state vector:
$x(t) = \left[x_l(t)\ \dot{x}_l(t)\ \theta(t)\ \dot{\theta}(t)\right]^T \in \mathbb{R}^4$, hence

$$\begin{aligned} E\left(x_l(t)\right)\dot{x}(t) &= A\left(x_l(t), \theta(t), \dot{\theta}(t)\right)x(t) + BF(t-\tau) \\ y(t) &= Cx(t), \end{aligned} \tag{2}$$

where $y(t) \in \mathbb{R}^2$ is the output of the system, the matrices are defined as follows:

$$A\left(x_l, \theta, \dot{\theta}\right) = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & -m_1 g\dfrac{\sin(\theta)}{\theta} & m_1 x_l\dot{\theta} \\ 0 & 0 & 0 & 1 \\ -m_1 g\cos(\theta) & -2m_1 x_l\dot{\theta} & \left(m_1 l_0 + m_2 l_c\right) g\dfrac{\sin(\theta)}{\theta} & 0 \end{bmatrix},$$

$$E\left(x_l\right) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & m_1 & 0 & -m_1 l_0 \\ 0 & 0 & 1 & 0 \\ 0 & -m_1 l_0 & 0 & m_1\left(l_0^2 + x_l^2\right) + m_2 l_c^2 \end{bmatrix},$$

$B = \begin{bmatrix}0 & 1 & 0 & 0\end{bmatrix}^T$, and $C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$.

Notice that the matrix $E\left(x_l\right)$ is regular, i.e., it is invertible $\forall x_l \in \mathbb{R}$ and one of the major point is that $\dot{\theta}(t)$ appearing in $A\left(\theta, x_l \times \dot{\theta}\right)$ is a non-measured variable.

2.2. Internal control

Model (1) being open-loop unstable, an internal control has to be designed in a way that the generalized stabilized model (see Fig. 2) is stable and allows designing an observer. In order to reproduce a human-like control, we need to take into account various delays: the transmission from sensor-to-controller and controller-to-actuator and also the electromechanical delay which represents the time for the muscle to generate force when receiving an electric impulse. Those delays are not constant, because they might depend on which muscle is activated and in what direction is given the information to the brain. Thus, we are faced to the control of a descriptor model with varying time delays on the control. The proposed approach is extended from a robust control of input delayed uncertain models (Yue and Han, 2005) using

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