

Biological and engineering approaches to human postural control

Karim Tahboub^{a,*} and Thomas Mergner^b

^a*College of Engineering and Technology, Palestine Polytechnic University, P.O. Box 103, Hebron, Palestine
Tel.: +972 599 656665; Fax: 972 2 2294036; E-mail: tahboub@ppu.edu*

^b*Neurological University Clinic, Neurocenter, University of Freiburg, Breisacherstr. 64, 79106 Freiburg, Germany
E-mail: mergner@uni-freiburg.de*

Abstract. This paper discusses the human postural control as an interdisciplinary problem. The goal of posture control is to maintain the orientation of the body upright. Two main approaches are presented to address the problem: neurological and engineering. Tackling the problem from the two perspectives aims to shed light on possible tools and techniques that may be borrowed from one field to the other. Accordingly, the two approaches are detailed first and then compared and linked. In the previously established neurological approach, the problem is described, main sensory systems are identified, sensor fusion is suggested, a control system architecture in most basic form is presented, and simulations and experiments on a special-purpose humanoid were performed yielding results similar to human performance. The engineering approach aims to yield a deeper understanding of the neurological perspective. In currently applied first steps regarding this approach, the humanoid parameters are identified, its dynamic model is derived, an external-disturbance estimation method is presented, a control concept for stabilizing the body motion and then for robust tracking of voluntary motion in the presence of external disturbances is shown in simulations. The simulation results demonstrate the validity and merits of this engineering approach. Finally, a comparison is made between the two approaches pointing out both, common and different features.

1. Introduction

Human upright stance is maintained by a posture control mechanism the goal of which is to maintain the orientation of the body upright and thereby the centre of mass (COM) above the base of the foot support. The mechanism may be impaired in several neurological diseases causing impairment of stance and locomotion. The maintenance of body uprightness during external disturbances is controlled mainly by a sensory negative feedback mechanism [6,8,21], which involves different sensory cues [5]. This notion was not without controversy until recently. Originally, it emerged from the idea to describe human experimental findings by means of engineering means [6,20]. A first attempt to directly compare human data with simulations of a feedback model was considered a failure. In a study

that measured loop gain of stance control in various experimental situations, the authors found a very low gain which they considered insufficient to explain postural stability [3]. They therefore concluded that the control is based not directly on sensory feedback, but on predictive mechanisms. Yet, more general performance data could be explained by multisensory feedback models [7,8,10]. Eventually, in an approach that postponed modelling of response non-linearities and sensory re-weightings it was shown that a multisensory feedback model is able to describe human responses to various external disturbances [21].

A different approach focused primarily on intersensory interactions in human self-motion perception, identified different sensor fusion mechanisms, and discovered that the same or analogous mechanisms can be found in sensorimotor control (overview [15]). When implementing these sensory interaction mechanisms as feedback into a human postural control model, the model could be used to describe human responses to

*Corresponding author.

various external disturbances including response nonlinearities and sensory re-weightings. In particular, it was possible to mimic the postural responses of normal subjects and vestibular loss patients to body support motion, pull stimuli having impact on the body, and visual scene motion as well as to account for automatic sensory re-weightings across changing stimulus conditions and to provide evidence for the involvement of a force control [12,16,18].

The latter work applied systems analysis methods in a biocybernetic ‘black box’ approach, which represents a (w)holistic approach. It aimed to reproduce the experimentally observed input-output relationships by the means of the simplest (parsimonious) formalism while respecting a number of constraints. The result was a control concept in which the sensory feedback is based on internal estimates of the external disturbances achieved by way of simple direct sensory interactions. In an attempt to ‘embody’ the discovered control concept, Mergner and colleagues devised a special purpose humanoid robot (“PostuRob”) which features a hardware-in-the-loop simulation environment for identifying postural control deficits in patients and the effects of therapeutic interventions as well as for designing new therapies [19].

Since balance control is a pre-requisite of stance and locomotion of bipeds, the control concept used in PostuRob may be of interest for other humanoid walking machines as well. To this end, it may be important to better understand the human control concept. This can possibly be tackled by using modern engineering methods. A mutual interaction between engineering and biological approaches will be beneficial for both fields. For instance, biologists may “borrow” new tools from the engineering field (compare [23]), and vice versa. As a first step into this direction, we proceed from the biological concept and try to select an engineering concept that would resemble it. To this end, we structured the engineering architecture as a combination of a tracking controller, a sensor fusion, and an estimation and a compensation of external disturbances. This structure relies on a widely accepted modern control methodology.

2. Biological concept, control problem, and experimental setup

The aim of neurological posture control studies is to understand the existing control processes and the causes of known abnormalities. This includes the identifica-

tion of sensory systems and components, the sensor fusion process, the control architecture and subsystems, and the actuators. Recently, there has been an effort to describe this medical knowledge (or theories) in terms of a mathematical description [8,21]. It is evident that the primary aim of the former studies is not to design a technical system, but to analyze and understand the behaviour of the human system. In this context, the experimental scenario should be limited to small whole body motion of leaning about the foot-ankle joint ($<6^\circ$) and should comprise volitional action (voluntary body lean) in the presence of external disturbances (force field, gravity; contact force, pull on the body; motion of support surface, platform tilt). Superposition of all external disturbances should be allowed while stable performance is still anticipated [17].

The multisensory posture control model of Mergner et al. [12,16,18] contains sensor fusions which the authors originally had derived from human kinematic perception studies during passive rotations of the body and its parts. From these psychophysical studies and related literature, they draw conclusions as to (1) the main sensors involved in human spatially oriented behaviour, (2) the principles of sensor fusion, and (3) the role of such sensor fusions in sensorimotor control mechanisms with feedback. For the latter, they choose as an especially simple prototype human control of upright stance since, with small body excursions, this control uses essentially only one joint (ankle joint; biomechanics: “inverted pendulum model”). The concepts were tested and approved by comparing the experimental biological data with model simulation data. In a further step (4), the sensorimotor control model was embodied into a biped humanoid, PostuRob. We highlight relevant points of this work:

1. *Sensors.* Conclusions about the involved sensors were drawn from experiments where sensors were selectively stimulated by natural means (e.g. motion) or artificial means (e.g. electric stimuli or vibration) or were non-functioning (e.g. patients) as well as on the basis of their response characteristics (in comparison with data from sensory physiology). They indicate a major role of four sensors:

- a) Inertial body motion sensors – Vestibular system. This system represents a 3D inertial “measuring device” for linear and angular body motion that receives sensory inputs from two receptor organs (macular and semicircular canal organs, respectively) encapsulated, and thus protected from contact forces deep within the bone of the head. Technical equivalents would essentially be a 3D

accelerometer and a 3D gyrometer, respectively. Central signal processing in the brain yields three measuring signals: 3D body rotational velocity, 2D body angle with respect to gravitational vector, and 3D body linear acceleration [13,24].

- b) Joint angle sensors – Ankle angle proprioception. Humans have a rather accurate sense of ankle joint position and velocity over a broad dynamic range, which stems mainly from stretch receptors in the related muscles and from receptors in the surrounding skin and in the joint capsules. A technical equivalent would be a goniometer (one that delivers both, position and velocity signals).
- c) Joint torque sensors – Ankle torque proprioception. Receptors allowing an estimate of joint torque include force receptors in the muscle tendons [2]. Also receptors in deep structures of the foot arch, from which a measure of COP (centre of pressure) shift can be derived, appear to be used for this purpose (compare [9]), at least in human posture control [11]. As technical equivalents, we used in PostuRob force sensors in the muscle mountings and a COP measure derived from force sensors under its forefeet and heels. (Force sensors were not considered in the psychophysical work).
- d) Visual sensors. Physiologically, visual sensors make considerable contributions to posture control. But their contributions are very complex and not yet fully understood. Furthermore, omitting vision during posture control does not yield major disadvantages. For these reasons we omit these sensors here.

The vestibular systems and the ankle angle systems are taken to represent broad band pass systems in the present context, whereas the ankle torque system is taken to represent a low-pass filtered system, and the ankle angle systems is taken to show clearly less noise than the two other systems (for details see [14]).

2. *Sensor fusion principles in the perception.* In biological research, the term sensor fusion is used for both, multisensory integration and intersensory interaction. The term multisensory integration is mostly used for a merging of two or more sensory signals stemming from the same physical event, but different sources (sensors), by which an improvement of the temporal and spatial resolution of the stimulus estimate is achieved (redundancy aspect; example: integration of visual and auditory inputs in neurons of the superior colliculus for targeting eye movements; see e.g. [22]). Intersensory interaction is more used for cooperative sensor fusion,

i.e. for a cooperation of sensors to derive information that neither sensor alone could provide (overview on intersensory interactions in spatially oriented behavior, where for instance a combination of object-eye (retinal), eye-head, and head-trunk signals are required for the planning of hand reaching movements [15]). Here we refer to the cooperative type of sensor fusion.

A major result on sensor fusion was that humans' self-motion perception reflects the physical stimulus event in the external world, which they estimate by combining the signals from several sensors (a single sensor signal does not sufficiently specify the stimulus). For instance, subjects perceive whether a vestibular signal during head-in-space rotation is experimentally evoked by passively rotating the head on stationary trunk (taking into account the associated neck proprioceptive signal), by rotating the body on stationary feet (leg proprioceptive signals), or by rotating the support surface the subject is standing on (no matching proprioceptive signal). Differences in the responses (frequency characteristics; gain and phase curves in Bode diagrams; amplitude characteristics; detection thresholds) across various stimulus conditions allow inferences on the underlying sensor fusion mechanisms and their formal description by means of cybernetic models (overview [15]).

In the perception modelling, software simulations were performed, searching for the most parsimonious model that would reproduce the response curves ("Occam's razor" rule: The most simple solution counts). Additional constraints were the sensor transfer characteristics and the models' modularity (applicability of fusion principles to other body segments and to multi-segment models). A particular feature in the findings, also covered by the models, was an automatic sensory re-weighting in the sense that the human self-motion perception stems primarily from proprioceptive and visual signals, which show little spontaneous variation over time (low noise), and involves vestibular signals (containing large low-frequency noise) only to the extent the support is moving [15].

3. *Sensor fusions in the sensorimotor control.* The fusion principles were implemented into an inverted pendulum model of human postural control of upright stance in the sagittal plane (Simulink, Matlab®). Kinetic aspects were added (effects of gravity and contact forces), fusion-derived estimation signals of the external disturbances were fed into a feedback loop, this loop was combined with a voluntary command set point signal, and finally a PID controller (P, proportional, I, integral, and D, derivative terms) was added, which

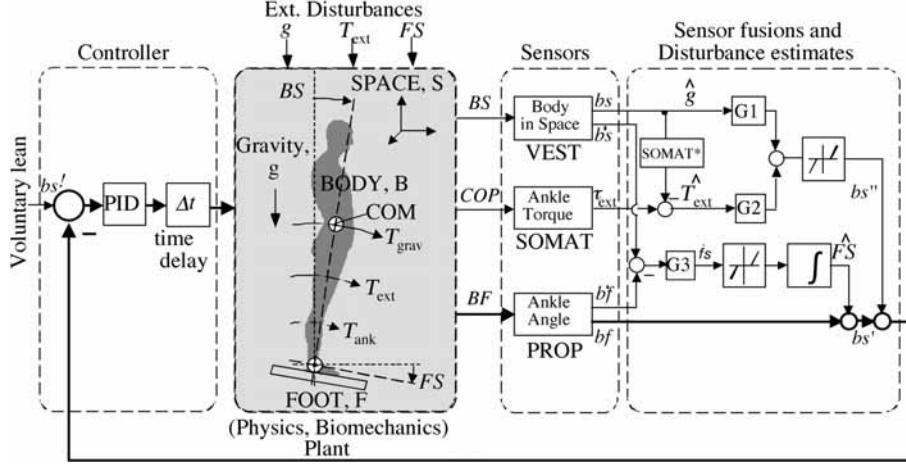


Fig. 1. Human posture control model. The external disturbances (estimates) are: g , gravitational vector (\hat{g}); T_{ext} , external contact force (\hat{T}_{ext}); FS , foot-space rotation during support-space rotation ($\hat{F}S$). The sensors are: VEST, vestibular sensor measuring 'Body in Space' angle, BS , and its velocity yielding signals bs and \dot{bs} (first derivative). SOMAT, somatosensory footsool pressure receptors transforming from the centre of pressure, COP, a measure of ankle torque, T_{ext} . PROP, ankle angle sensor providing measures of body-foot angle and its velocity, bs and \dot{bs} . G_1 and G_2 , gain factors transforming kinetic estimates into kinematic equivalent; threshold describes non-linear amplitude response behavior to pull stimuli. G_3 , gain factor of foot-space velocity signal ($\dot{f}s = \dot{bs} - \dot{bf}$), from which the foot-space estimate $\hat{F}S$ is derived following a biologically motivated threshold and an integration. These estimates upgrade the proprioceptive body-foot (bf) feedback loop into a body-space (bs') loop.

was taken to produce ankle joint torque by means of actuators (assumed to be essentially ideal for the task considered here). The model was tested by comparing the experimental biological data (subjects' postural responses during external disturbances) with the model's simulation data, model parameters were identified, and quality of data fit was taken to approve the validity of the model [12,16,18].

The model is shown in Fig. 1. The main points which the model makes are (i) that the complex human sensorimotor control mechanisms can be "prototyped" in an extremely simple behavioral scenario (allowing physics to be modeled by an inverted pendulum model), (ii) that the external physical disturbances are internally estimated by means of multi-sensory fusions, (iii) that these estimates are used for disturbance compensation by feeding them into a body-foot angle proprioceptive feedback loop (transforming it into a body-space control), and (iv) that force disturbances together with position disturbances and a body-space voluntary set point signal (Voluntary lean, bs') can be combined in the control. The external disturbances of the 'inverted pendulum' (box 'Plant') are gravity (g), external contact force (T_{ext} , applied in the form of a pull on the body), and support surface tilt leading to foot-in-space tilt (FS) with the tilt axis in the ankle joint. Support surface and body translations are presently omitted in order to not obscure the basic function principles. In the box 'Sensors', body-in-space rotation (BS) is

sensed by the vestibular system (VEST, yielding a sensor position signal bs and velocity signal \dot{bs}). Body angle with respect to the foot (BF) is sensed by ankle angle proprioception (PROP; bf and \dot{bf}). A measure of ankle joint torque is calculated from the COP shift and somatosensory force receptors in the feet (SOMAT; τ_{ank}).

Estimates of the external disturbances g , T_{ext} , and FS (\hat{g} , \hat{T}_{ext} , $\hat{F}S$) are obtained in the box 'Sensor fusion and Disturbance estimates'. The estimate of the gravitational torque effect \hat{g} , is derived from the vestibular bs signal. The contact force estimate \hat{T}_{ext} is obtained by decomposing the ankle torque signal, removing from it, with the help of vestibular signals, the dynamic and static torque components that arise with body excursion BS (box 'Somat*'). The two kinetic estimates \hat{g} and \hat{T}_{ext} are transformed by factors (G_1 , G_2) into kinematic equivalents of BS excursions, summed, and passed through a position threshold. The kinematic estimate $\hat{F}S$ is taken from vestibular and proprioceptive velocity signals (velocity was suggested by biological data) in the form of $\dot{f}s = \dot{bs} - \dot{bf}$, which is followed by a velocity threshold and an integration.

The disturbance estimate f_s is fed into a kinematic body-foot angle feedback control loop (via signal bf), which thereby becomes upgraded into a body-in-space control loop ($bs' = bf + f_s$), before the bs'' equivalent for the torque estimates and the set point signal (bs') is added. Here, kinematic control is thought to have

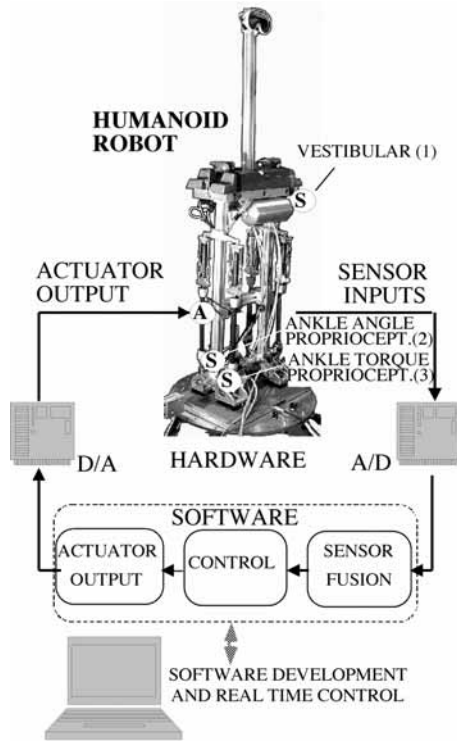


Fig. 2. Hardware-in-the-loop simulation of biped upright stance using a humanoid robot (photograph of 'PostuRob') freely standing on a motion platform. A, actuators consisting of pneumatic muscles; S, sensors consisting of vestibular (1), ankle joint angle (2), and ankle joint torque (3) sensors.

primacy involving conscious perception, planning, etc. via the cerebral cortex, while kinetic aspects are thought to mainly involve unconscious secondary mechanisms via the cerebellum. The thresholds in the model mimic biologically observed amplitude non-linearities. Δt in the controller box (150 ms) is used to lump together all dead and delay times of the system.

Noticeably, the sensor fusion of the support tilt estimate \hat{FS} yields an automatic sensory re-weighting. The underlying signal fs is zero when subject stands on stationary support; the vestibular contribution bs is cancelled by the proprioceptive contribution bf and large low-frequency noise of the vestibular signals is suppressed by the subsequent threshold. The signal bs' is then determined by bf alone. In contrast, upon platform tilt, bs' becomes mainly determined by vestibular input \dot{bs} with its large noise, since then its two proprioceptive contributions from bf and \dot{bf} largely cancel each other.

For simulations of the model, we refer to the previous studies [12,16,18]. The model of Fig. 1 does not yet account for all currently known biological findings

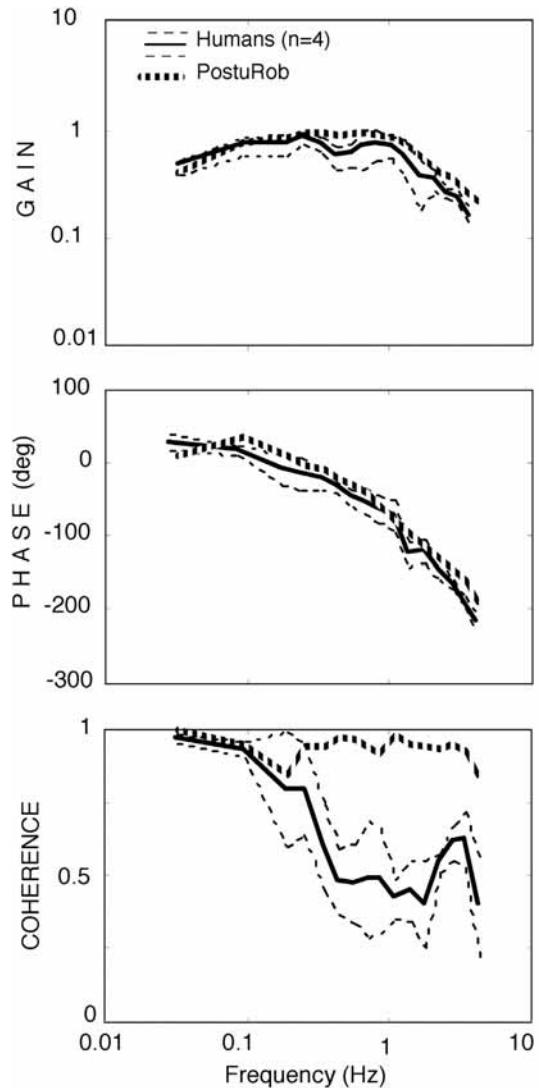


Fig. 3. PostuRob's postural frequency responses to platform tilt. The gain and phase responses versus stimulus frequency as well as coherence obtained with a pseudorandom ternary stimulus profile are shown. In each panel PostuRob's data is superimposed on the averaged data of four normal human subjects.

on human posture control, but it accounts for major findings concerning the sensors, sensor fusions and reduction of vestibular noise. In this sense, it represents a parsimonious solution for 'making the scientific point' which is that adding engineering tools to this field of research allows to describe human postural control better than hitherto possible.

4. *Embodiment of principles into humanoid.* The model of Fig. 1 represents the blueprint for PostuRob's control. It is implemented in a Simulink version on an embedded PC under the control of a host PC. The

robot's hardware consists of the above described sensors and related electronics. Furthermore, it consists of an aluminum skeleton with two feet and two rigid legs fixed to a pelvic girdle and a spine ('body'). Centre of mass (COM) is mainly represented by two lead weights on the pelvis. Each leg carries a front and back pneumatic 'muscle' with 'tendons' (springs) to move the body with respect to the foot about the 'ankle joint'. The robot (Fig. 2) is freely standing on a motion platform that can be tilted about the ankle joints. Technical specifications are given under www.uniklinik-freiburg.de/neurologie/live/forschung/sensorfusion/PostuRob.html.

In order to achieve an essentially 'ideal actuator' for the performance of the muscle-tendon system in the considered scenario, a cascaded control with air pressure and tendon force feedback was used. By this, we conceived that there may exist a mechanism in the human spinal cord that accounts for non-optimal actuator characteristics (e.g. non-linearities) and allows for a single controller (to simplify and unify the supraspinal control across many possible input sources).

PostuRob is able to perform 'voluntary' body lean movements while, at the same time, support tilt and external force stimuli are applied. Upon adjusting the PID factors, gain and phase curves of platform tilt responses closely mimic those of humans (Table 1). With this, control gain is so low that tilt and pull stimuli are 'human-like' under-compensated. This also applies to gravity compensation, requiring a scaling of the voluntary command signal by a factor of 1/3–1/4 for correct voluntary leans. The low gain allows for delays of the system well above 100 ms and make the overall control very "soft" and compliant. This is brought about by the system's architecture, which can be viewed as containing an "internal feed forward disturbance compensation". By this architecture, a given disturbance estimate increases the loop gain only to the extent that the corresponding disturbance is currently occurring. This applies independently of whether the disturbance is a kinetic one, requiring a torque compensation for maintaining upright stance, or a kinematic one, requiring a compensatory change in body-to foot angle BF .

To characterise PostuRob's postural responses to platform tilt we show in Fig. 3 response gain and phase over stimulus frequency (Bode plots) as well as coherence obtained with a pseudorandom ternary stimulus profile (see [21]). Experimental PostuRob's data in the figure is superimposed on the averaged data of four normal human subjects. The two data sets resemble each other closely and furthermore resemble previously

published human data in the literature [21]. Similar data (not shown) were obtained for voluntary lean as input and for responses to pull stimuli (albeit with lower gain, i.e. smaller body excursions; compare [12]). Furthermore, we show in Fig. 4 PostuRob's experimental responses in a situation where it performed voluntary lean movements (panel A; $\pm 2^\circ$, smoothed square waves at 0.075 Hz) while, intermittently, the support platform was tilted (panel B; $\pm 2^\circ$, sine wave stimulus at 0.2 Hz). Comparisons between actual and estimated body-foot and body-space angles are given in panels C and D.

PostuRob's human-like performance qualifies it to be used for developing neurological diagnostic and therapeutic tools using a hardware-in-the-loop simulation approach. The fact that it is rather robust against sensor failure and inaccurate control signals may allow to also use it as a multi-purpose humanoid robot in other applications. Its explicit estimates of the external disturbances create a meta-level that allows for communicating information of the outside world with other robots, storing the information, etc. Future developments of it will focus on the modularity of the system by adding further body segments, control features and sensory re-weighting mechanisms. Furthermore, support translation as an external disturbance will be included. In the present form, PostuRob does not identify this stimulus, rather compensates it to the extent that an ankle torque results from it (due to body inertia), which is estimated as an external force stimulus.

The embodiment of the control concepts into real world media and the hardware-in-the-loop (HIL) simulation brought about a confrontation with non-ideal sensor functions and with signal noise, offsets, and drifts from many sources, often slightly changing 'spontaneously' over time and not always foreseeable. In this respect, it is more 'natural' than simulations with pure software models. In its current form, both the architecture (structure) and the parameters await closer inspection and analyses using mathematical models and modern control theory techniques.

3. Control engineering approach

A traditional model-based control approach is selected to tackle the posture control problem. The aim of the current study is to design a state and disturbance estimator as well as to design a controller that is capable of stabilizing the system and achieving desired voluntary motion even in the presence of the above men-

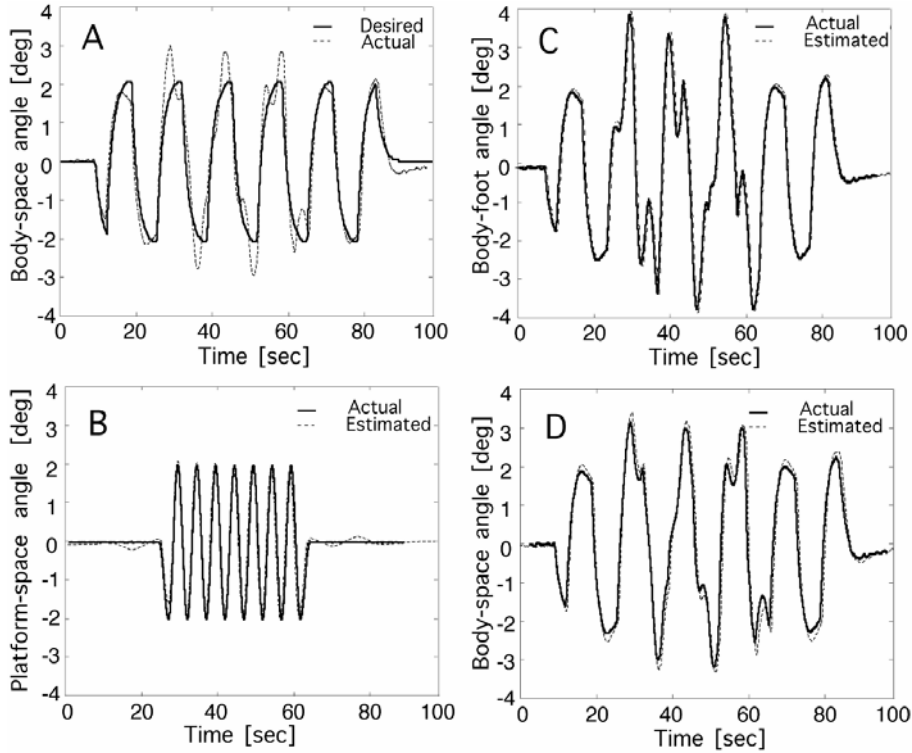


Fig. 4. PostuRob's postural time response to voluntary lean and platform tilt stimuli. The desired and actual voluntary motion is shown in panel A ($\pm 2^\circ$, smoothed square waves at 0.075 Hz); the actual and estimated platform tilt is shown in panel B ($\pm 2^\circ$, sine wave stimulus at 0.2 Hz); comparisons between actual and estimated body-foot and body-space angles are given in panels C and D.

tioned disturbances. As mentioned before, the ultimate goal of this part is not the control of the humanoid itself but the comparison with the human control to yield a deeper understanding of the neurological perspective. For this, the humanoid is fully modeled as two rigid bodies (the foot and the body) connected together with a revolute joint (ankle joint) and actuated with pneumatic actuator 'muscle' (front and back sides) that apply forces on the body and reaction forces on the foot; the front and back forces produce the actuating torque. The foot rests on a movable (tilting) platform (the same used for testing human subjects). The same sensors as before are available. For instance, two foot reaction forces due to the weight and the dynamic forces can be measured by force sensors. Since the platform is allowed to tilt and external forces are allowed to pull the body, a friction (or shear) force between the foot and the platform is anticipated. The centers of mass of the foot and of the body are assumed to have some eccentricity from the vertical centerline passing through the joints. Figure 5 shows the two rigid bodies, the actuators and the main acting forces.

3.1. Modelling

The major forces acting on the humanoid are shown in Fig. 5. These include the reaction forces F_F and F_B , the friction force beneath the foot, the weight of the two segments, the centrifugal and the inertia forces. The body angular acceleration can be obtained by summing the active moments about the joint. This yields the main equation of motion (see Tables 2, 3):

$$I_2 \ddot{\alpha} = -F_1 D + F_2 D + F_e (h_e - d \cos(\theta)) + M_2 L \sin(\alpha + \theta - \gamma) \quad (1)$$

where an external force F_e is considered to be acting on the body and where the platform is tilted off the horizontal with an angle θ (and its corresponding angular velocity and acceleration $\dot{\theta}$, $\ddot{\theta}$). Here it is assumed that the platform tilt is passing through the joint although in reality it may often be passing just beneath the foot. Notice that the effect of the platform tilt appears directly as a gravitational destabilizing force.

The force sensors give valuable information about the system and the external disturbances acting on it. First, the summation of the normal forces (reaction

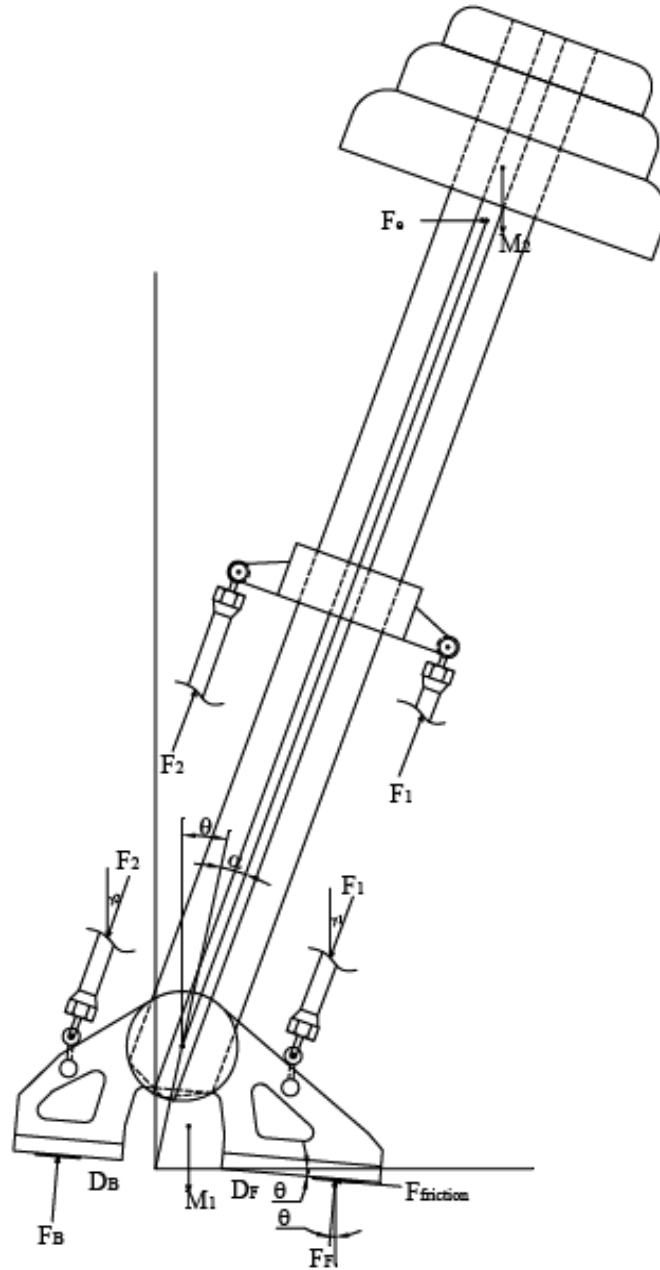


Fig. 5. Main forces acting on the humanoid (drawing is not to scale).

forces normal to the contact surface), measured by the plantar somato-sensory force sensors, is obtained by summing up the forces acting on the whole system:

$$\begin{aligned}
 F_F + F_B = & (M_1 + M_2) \cos(\theta) - F_e \sin(\theta) \\
 & - m_2 L (\ddot{\alpha} + \ddot{\theta}) \sin(\alpha - \gamma) \\
 & - m_2 L (\dot{\alpha} + \dot{\theta})^2 \cos(\alpha - \gamma)
 \end{aligned} \quad (2)$$

Definition of variables is done in Table 3. Here, the sum is composed of the total weight projected vertically on the platform, together with the vertical component exerted by the external force as well as the translational effect of the angular velocity and acceleration of the body. Furthermore, the moment of these normal forces (which is related to the COP) is

Table 1

Comparison of model parameters between humans (from Maurer et al. 2006) and PostuRob. NC, Neural Controller

Parameter	Humans	PostuRob
Proportional part of NC [Nm/deg]	15.1	16.2
Derivative part of NC [Nm*s/deg]	4.40	4.9
Integral part of NC [Nm/(s*deg)]	1.33	0.96
Time delay [s]	0.17	0.14
Passive stiffness [Nm/deg]	0.91	–
Passive damping [Nm*s/deg]	0.68	–
Gain of $\dot{F}S$ (G3)	0.79	0.9
Threshold of f_s signal [deg/s]	0.17	0.18
Gain of \hat{g} (G1)	1.52 (G1 + G2)	0.9
Gain of T_{ext} (G2)	–	0.8
Threshold of bs'' [deg]	0.17	0.16

$$\begin{aligned}
D_F F_F - D_B F_B &= M_1(h_1 \sin(\theta) + w_1 \cos(\theta)) \\
&+ M_2 d \sin(\theta) + F_e d \cos(\theta) - m_2 L d (\ddot{\alpha} + \ddot{\theta}) \\
&\cos(\alpha - \gamma) + m_2 L d (\dot{\alpha} + \dot{\theta})^2 \sin(\alpha - \gamma) \\
&+ F_1 \cos(\gamma_1) D - F_2 \cos(\gamma_2) D
\end{aligned} \quad (3)$$

whereas, the horizontal friction (shear) force is given as:

$$\begin{aligned}
F_{friction} &= (M_1 + M_2) \sin(\theta) + F_e \cos(\theta) \\
&- m_2 L (\ddot{\alpha} + \ddot{\theta}) \cos(\alpha - \gamma) \\
&+ m_2 L (\dot{\alpha} + \dot{\theta})^2 \sin(\alpha - \gamma)
\end{aligned} \quad (4)$$

Furthermore, the vestibular sensor (for simplicity, only an accelerometer is considered here, as long as explicit estimates of support rotation and translation are not demanded) is placed at the known height h_a . It provides two orthogonal acceleration quantities; these can be transformed to absolute coordinates to yield:

$$\begin{aligned}
a_x &= g \sin(\alpha + \theta) + (\ddot{\alpha} + \ddot{\theta}) h_a \\
a_y &= g \cos(\alpha + \theta) + (\dot{\alpha} + \dot{\theta})^2 h_a
\end{aligned} \quad (5)$$

where g is the gravitational acceleration constant.

The angular velocity and acceleration of the platform and of the body appear in the above four equations whereas the external force appears only in the first three equations. Moreover, the acceleration measurements do not depend on any system parameter except the height of the sensor. Finally, the angle α is measured by the joint-angle sensor.

3.2. Linearization

Since the voluntary motion is limited to a few degrees around the upright stance and since the platform tilting angle is confined to small changes about the upright stance orientation and its motion can be considered

quasi static, the equations describing the dynamics of the humanoid can be linearized to yield:

$$\begin{aligned}
I_2 \ddot{\alpha} &= -F_1 D + F_2 D + F_e (h_e - d) \\
&+ M_2 L (\alpha + \theta - \gamma)
\end{aligned} \quad (6)$$

$$F_F + F_B = (M_1 + M_2) - F_e \theta + m_2 L \gamma \ddot{\alpha} \quad (7)$$

$$\begin{aligned}
D_F F_F - D_B F_B &= M_1 (h_1 \theta + w_1) + M_2 d \theta \\
&+ F_e d - m_2 L d \ddot{\alpha} + F_1 D - F_2 D
\end{aligned} \quad (8)$$

$$F_{friction} = (M_1 + M_2) \theta + F_e - m_2 L \ddot{\alpha} \quad (9)$$

$$\begin{aligned}
a_x &= g (\alpha + \theta) + \ddot{\alpha} h_a \\
a_y &= g
\end{aligned} \quad (10)$$

These equations, which represent a linear time-invariant system, can be expressed in state-space form as:

$$\begin{aligned}
\underbrace{\begin{bmatrix} \dot{\alpha} \\ \ddot{\alpha} \end{bmatrix}}_{\dot{x}} &= \underbrace{\begin{bmatrix} 0 & 1 \\ \frac{M_2 L}{I_2} & 0 \end{bmatrix}}_A \underbrace{\begin{bmatrix} \alpha \\ \dot{\alpha} \end{bmatrix}}_x + \underbrace{\begin{bmatrix} 0 \\ \frac{1}{I_2} \end{bmatrix}}_B \underbrace{T}_u \\
&+ \underbrace{\begin{bmatrix} 0 \\ \frac{M_2 L}{I_2} \end{bmatrix}}_{H_1} \theta + \underbrace{\begin{bmatrix} 0 \\ \frac{h_e - d}{I_2} \end{bmatrix}}_{H_2} F_e - \underbrace{\begin{bmatrix} 0 \\ \frac{M_2 L}{I_2} \end{bmatrix}}_{H_3} \gamma
\end{aligned} \quad (11)$$

where the first part ($\dot{x} = Ax + Bu$) describes a linear system superimposed by the effect of external disturbances (θ, F_e, γ). Note that the eccentricity in the body's COM (represented by γ) causes a tip over effect. Furthermore, all possible measurements can be represented in matrix form:

$$\begin{aligned}
\mathbf{y} &= \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \end{bmatrix} = \begin{bmatrix} \alpha \\ \dot{\alpha} \\ a_x \\ D_f F_F - D_B F_B \\ F_{friction} \end{bmatrix} \\
&= \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ g + M_2 L h_a / I_2 & 0 \\ -m_2 M_2 L^2 d / I_2 & 0 \\ -m_2 M_2 L^2 / I_2 & 0 \end{bmatrix} \begin{bmatrix} \alpha \\ \dot{\alpha} \end{bmatrix} \\
&+ \begin{bmatrix} 0 \\ 0 \\ h_a / I_2 \\ 1 - m_2 L d / I_2 \\ -m_2 L / I_2 \end{bmatrix} [T]
\end{aligned} \quad (12)$$

$$\begin{aligned}
& + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ g + M_2 L h_a / I_2 & (h_e - d) h_a / I_2 \\ M_1 h_1 d + M_2 d - & L d (h_e - d) / I_2 \\ m_2 M_2 L^2 d / I_2 & d - m_2 \\ M_1 + M_2 - m_2 & 1 - m_2 \\ M_2 L^2 / I_2 & L (h_e - d) / I_2 \end{bmatrix} \\
& \begin{bmatrix} \theta \\ F_e \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ -M_2 L h_a / I_2 \\ m_2 M_2 L^2 d / I_2 \\ m_2 M_2 L^2 / I_2 \end{bmatrix} [\gamma] + \begin{bmatrix} 0 \\ 0 \\ 0 \\ M_1 w_1 \\ 0 \end{bmatrix}
\end{aligned}$$

3.3. Parameter estimation

For using the above model in control, all geometric and mass parameters must be measured or identified. Since the working range of the humanoid is limited to a few degrees of rotation about the equilibrium position, it becomes demanding to employ dynamic system identification techniques. Alternatively, a set of “static” experiments are designed to measure and identify the humanoid parameters in static postures. These experiments include the inclination of the body and/or tilting the platform with known angles ranging from 1 to 4 degrees. Platform normal reaction forces and applied torque are measured for each experiment. The results are averaged to yield the parameters given in Table 2. It is noted that the mass moment of inertia cannot be identified by static measurements, so it is assumed that the mass of the body is concentrated in its center to have an approximate value for the mass moment of inertia.

3.4. Estimation of external disturbances

The main difficulties which control faces here are the nonlinear dynamics as presented in the above equations and the presence of external disturbances that are not directly measurable. Since foot-ankle angle (and its angular velocity), an acceleration at a known point, and reaction forces are measurable, then it should be theoretically possible to estimate these external disturbances including the pull force and the platform tilt. The estimation can be done either by solving the equations for the unknown variables or by the means of an extended observer. The former option requires solving the nonlinear equations numerically since an analytical solution is difficult to obtain. The latter option can be realized using the linearized dynamics model. This option is chosen as it resembles a systematic system-theory approach. The same tools used here can be em-

ployed for higher dimensional systems including more body segments and more degrees of freedom.

An extended observer is basically a classical observer where the external disturbances are assumed to be regular states [4]. Here, the platform tilt angle θ and the external pull force F_e are assumed to be the third and fourth states. However, since these states are originally extraneous to the system, one cannot write down their corresponding differential equations governing their behavior in the time domain, which is necessary for completing the extended state-space model. A practical solution would be to assume that they are step-wise constant or quasi static. That is their derivatives are set to zero. These assumptions lead to the following linear state-space representation:

$$\begin{aligned}
\underbrace{\begin{bmatrix} \dot{\alpha} \\ \ddot{\alpha} \\ \dot{\theta} \\ \dot{F}_e \end{bmatrix}}_{\dot{x}_e} &= \underbrace{\begin{bmatrix} 0 & 1 & 0 & 0 \\ \frac{M_2 L}{I_2} & 0 & \frac{M_2 L}{I_2} & \frac{h_e - d}{I_2} \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}}_{A_e} \underbrace{\begin{bmatrix} \alpha \\ \dot{\alpha} \\ \theta \\ F_e \end{bmatrix}}_{x_e} \\
& + \underbrace{\begin{bmatrix} 0 & 0 \\ \frac{1}{I_2} & -\frac{M_2 L}{I_2} \\ 0 & 0 \\ 0 & 0 \end{bmatrix}}_{B_e} \underbrace{\begin{bmatrix} T \\ \gamma \end{bmatrix}}_{T} \quad (13)
\end{aligned}$$

The extended-state vector comprised of $\alpha, \dot{\alpha}, F_e$ and θ can be estimated given the measurements, if and only if the pair (A_e, C_e) is observable. It is straight forward to prove that it is observable given the measurements y_1 to y_5 . As a matter of fact, it is not necessary to employ all measurements to achieve this observability condition as the extended system is observable given any two simultaneous measurements out of the measurements $\alpha, a_x, D_F F_F - D_B F_B$, and F_{friction} . The measurement $\dot{\alpha}$ can additionally be used if sensor noise is considered. For this work, a set of full-order observers are tested, with the difference between the real measurements and the observer-generated measurements being feedback to force the estimation error to converge to zero with any desired speed. The assumption that the external disturbances are step-wise constant calls for a fast observer whose time constants are shorter than those constant steps to be able to catch the real changes in the external disturbances. Finally, it is stated here that the initial conditions of neither the plant nor the estimator are necessary for the estimation process.

Table 2
Humanoid Parameters

Parameter	Meaning	Value	Unit
m_1	Mass of foot	8.6349	kg
m_2	Mass of body	90.724	kg
M_1	Weight of foot	84.7	N
M_2	Weight of body	890	N
D_F	Front force sensor distance to centerline of foot	0.1475	m
D_B	Back force sensor distance to centerline of foot	0.1025	m
h_1	Height of foot COM	0.0360	m
w_1	Eccentricity of foot COM	0.0121	m
h_2	Height of body COM	0.8500	m
w_2	Eccentricity of body COM	0.0018	m
h_a	Height of vestibular sensor set	0.8000	m
L	Distance to body COM	0.8500	m
d	Height of foot-ankle joint	0.1080	m
D	Distance from centerline to actuating force point of application	0.1000	m
D_c	Height from foot-ankle joint to actuating force point of application on body	0.4230	m
γ	Eccentricity angle of body COM from centerline; ($\tan(\gamma) = w_2/h_2$)	0.0021	rad

$$\begin{aligned}
\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ y_4 \\ y_5 \\ y_6 \end{bmatrix} &= \begin{bmatrix} \alpha \\ \dot{\alpha} \\ a_x \\ D_f F_F - D_B F_B \\ F_{\text{friction}} \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ g + M_2 L h_a / I_2 & 0 & g + M_2 L h_a / I_2 & (h_e - d) h_a / I_2 \\ -m_2 M_2 L^2 d / I_2 & 0 & M_1 h_1 d + M_2 d - m_2 M_2 L^2 d / I_2 & d - m_2 L d (h_e - d) / I_2 \\ -m_2 M_2 L^2 / I_2 & 0 & M_1 + M_2 - m_2 M_2 L^2 / I_2 & 1 \end{bmatrix}}_{C_e} \\
&+ \underbrace{\begin{bmatrix} 0 & 0 \\ 0 & 0 \\ h_a / I_2 & -M_2 L h_a / I_2 \\ 1 - m_2 L d / I_2 & m_2 M_2 L^2 d / I_2 \\ -m_2 L / I_2 & m_2 M_2 L^2 / I_2 \end{bmatrix}}_{D_e} \begin{bmatrix} T \\ \gamma \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ M_1 w_1 \\ 0 \end{bmatrix} \quad (14) \\
&\underbrace{\begin{bmatrix} \alpha \\ \dot{\alpha} \\ \theta \\ F_e \end{bmatrix}}_{x_e}
\end{aligned}$$

3.5. Control law

The effect of the disturbances acting on the system, namely F_e and θ , can be theoretically cancelled by statically compensating for them. This is possible as their estimates \widehat{F}_e and $\widehat{\theta}$ can be obtained by the means of the extended observer and as they act as external disturbing torques. Thus, one can dedicate a part of the actuating torque T to the purpose of disturbance cancellation. The result of this is a simple linear system of second order. Here different control strategies can be thought of. However, since the biologically findings would be compatible with a PID controller, it will be selected here as well. However, a different interpretation is given to this controller; it is viewed as a classical robust tracking and disturbance rejection mechanism where the desired input to be tracked is a step input requiring an integral internal model. The PD part is seen as the required state-feedback control

inner loop. In summary, the control input T has two parts: the first, T_d , compensates for the external disturbances while the second, T_i , achieves robust tracking and further disturbance rejection:

$$\begin{aligned}
T &= - \underbrace{(\widehat{F}_e (h_e - d) + M_2 L (\widehat{\theta} - \gamma))}_{T_d} \\
&\quad - \underbrace{(k_p \alpha + k_d \dot{\alpha} + k_i \int (\alpha_d - \alpha) dt)}_{T_i} \quad (15)
\end{aligned}$$

where α_d is the desired ‘‘voluntary’’ body motion and \widehat{F}_e and $\widehat{\theta}$ denote the estimates of F_e and θ respectively. k_p , k_d , and k_i denote the position (proportional), velocity (derivative), and robust tracking (integral) feedback gain respectively [1]. To find the required gains, an augmented system comprised of the two states α and $\dot{\alpha}$ together with a third state corresponding to the integral

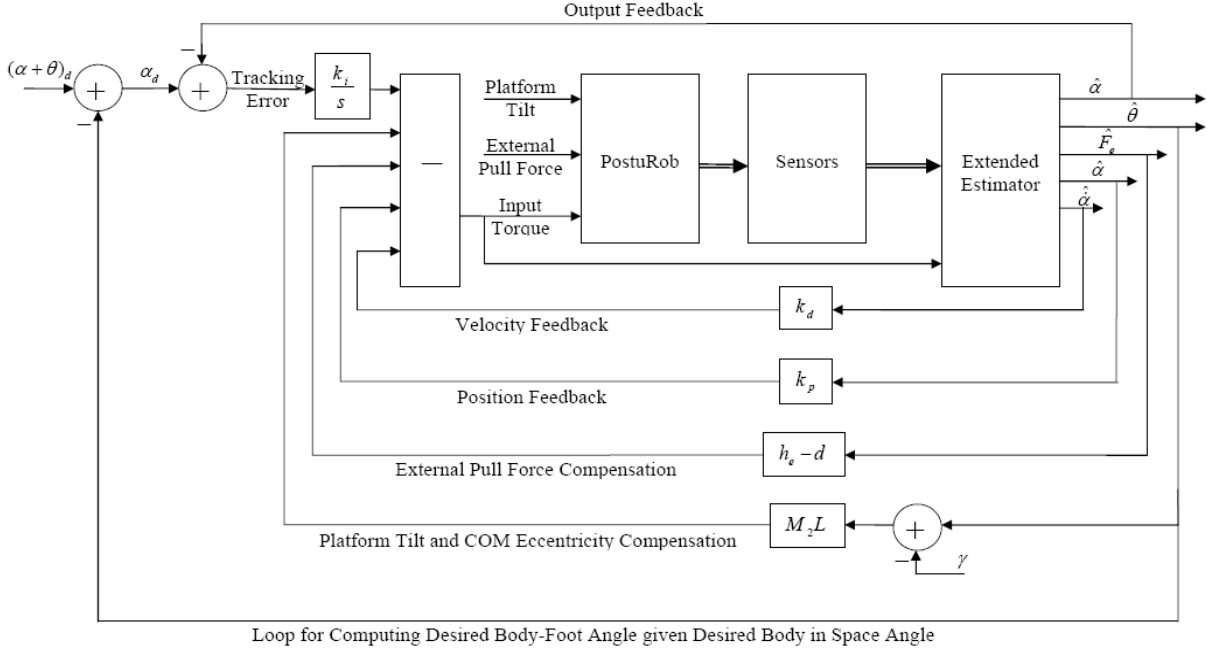


Fig. 6. Control architecture and simulation model showing the plant, extended observer, estimated-disturbances compensation, state-feedback inner loop, and internal model integral controller.

of the tracking error, is used:

$$\begin{bmatrix} \dot{\alpha} \\ \ddot{\alpha} \\ \alpha_d - \alpha \end{bmatrix} = \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & 1 & 0 \\ M_2 L / I_2 & 0 & 0 \\ -1 & 0 & 0 \end{bmatrix}}_{A_a} \underbrace{\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}}_{x_a} + \underbrace{\begin{bmatrix} 0 \\ 1/I_2 \\ 0 \end{bmatrix}}_{B_a} T + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \alpha_d \quad (16)$$

where A_a and B_a are the augmented states and input matrices respectively. The augmented state vector, x_a , is controllable as the augmented pair (A_a, B_a) is controllable for any values of the parameters. This means the dynamics of the tracking error and of the first two states can be chosen arbitrarily by the means of feedback gains. These gains are found by solving either a pole-placement or an optimal control problem given the augmented model. Since a voluntary motion is usually specified relative to an absolute frame (rather than relative to the platform), the summation of α and θ becomes the reference input. For this, the desired α_d is obtained by subtracting the estimated platform tilt angle $\hat{\theta}$ from the desired reference. The corresponding simulation model is shown in Fig. 6.

3.6. Simulation experiments

To test the validity and to study the performance of the introduced control and estimation strategy, several simulation experiments are designed. It is desired that the body moves voluntarily in the absolute space according to a pre-specified function:

$$(\alpha + \theta)_{\text{desired}} = 3^\circ \sin(0.2\pi t) \quad (17)$$

in the presence of a sinusoidally-tilting platform where its motion is given by:

$$\theta = 3^\circ \sin(0.4\pi t) \quad (18)$$

and an external pulse pull force F_e with a magnitude of 30 N and a duration of 5 sec. The two motions are selected to have different frequencies to excite a non-constant amplitude body angular motion. Further, a time delay of 100 ms is assumed at the controller-actuator side and a saturation of 100 N.m is imposed on the actuator. To this end, the whole system comprising the nonlinear plant, the extended estimator, and the robust tracking and disturbance compensator is built using the SIMULINK environment (see Fig. 6).

The closed-loop poles of the augmented system are chosen in such a way as to yield approximately the same feedback gains identified in human control:

Table 3
Humanoid Variables

Variable	Biological Equivalent	Meaning	Unit
$F_{friction}$		Friction force between foot and platform	N
F_F		Measured reaction force at the foot front	N
F_B		Measured reaction force at the foot back	N
F_e	$\approx T_{ext}$	External pull force (disturbance)	N
F_1		Front actuating force	N
F_2		Back actuating force	N
T	T_{ank}	Torque applied at the body $T = (F_2 - F_1)D$	N.m
α	bf	Body angle relative to foot	rad
$\dot{\alpha}$	\dot{bf}	Body angular velocity relative to foot	rad/s
$\ddot{\alpha}$	\ddot{bf}	Body angular acceleration relative to foot	rad/s ²
γ_1		Front actuator angle $\tan(\gamma_1) = \frac{D_c \sin(\alpha) + D(\cos(\alpha) - 1)}{D_c \cos(\alpha) - D \sin(\alpha)}$	rad
γ_2		Back actuator angle $\tan(\gamma_2) = \frac{D_c \sin(\alpha) + D(1 - \cos(\alpha))}{D_c \cos(\alpha) + D \sin(\alpha)}$	rad
θ	fs	Platform tilt angle (external disturbance)	rad
h_e		Height of external pull force application point	m
a_x		Measured tangential acceleration perpendicular to the COM line and pointing to the right	m/s ²
a_y		Measured normal acceleration and pointing inwards	m/s ²

$$\begin{bmatrix} k_p \\ k_d \\ k_i \end{bmatrix} = \begin{bmatrix} 928 \\ 280 \\ -57 \end{bmatrix} \quad (19)$$

On the other hand, the eigenvalues of the extended estimator are chosen to be faster than those of the closed-loop controlled system to guaranty “real-time” estimation convergence. The same eigenvalues are used for a set of observers using different measurements. Stability and convergence are demonstrated in all experiments even in the presence of measurement noise.

Employing the body-foot angle measurements together with any other measurement yields good estimation results such that the estimates converge to the value of the actual disturbances in real time. The tracking controller works well such that the body-foot angle tracks the specified desired “voluntary” motion. Simulation results corresponding to employing the normal and shear force measurements, show that the estimates of the disturbances are close enough to the actual disturbances with a clear error (peak) at the moments of applying the external force (figures are not shown for space limitations). The controller guaranties the tracking of the desired voluntary motion, α , with a certain phase lag. This phase lag depends on the controller gains as well as the time-delay inserted between the controller and the actuators. The tracking of the voluntary motion in space, $\alpha + \theta$, is achieved with some errors that depend on the former tracking error and on the platform tilt. Employing the acceleration measurement improves the estimation in general and eliminates the existence of the mentioned peak errors (see Fig. 7). The tracking errors remain the same. It is noted that

employing all measurements at the same time does not improve the estimation any further.

Finally, the effect of measurements noise is investigated. A white noise of about 10% of the signal amplitude is added to all measurements. The control system is proved to be robust against measurement noise especially against the non-force measurements. However, it is noticed that in the performance deteriorates when the force sensors become too noisy. Figure 8 shows simulation results the presence of measurement noise assuming that the acceleration sensor is used. It is noted that the very noisy desired α motion is the result in of the estimation error of the platform tilt. However, the actual motion is not contaminated with this noise as the humanoid and actuator dynamics filter this noise out as the physical system has a limited bandwidth that cannot respond to ultra high frequency desired motion.

4. Discussion, conclusion, and further work

In this article, the human posture control problem has been tackled from neurological and engineering perspectives. The main goal of considering the engineering perspective is to explore the possibility of gaining more insight into the problem while benefiting from well-established engineering techniques and methodologies. Thus, the engineering presented approach is not meant to replace the neurological understanding or to compete with it but rather to augment it. It is believed that joining the two fields is synergetic to each of them. Applying engineering tools would polish the neurolog-

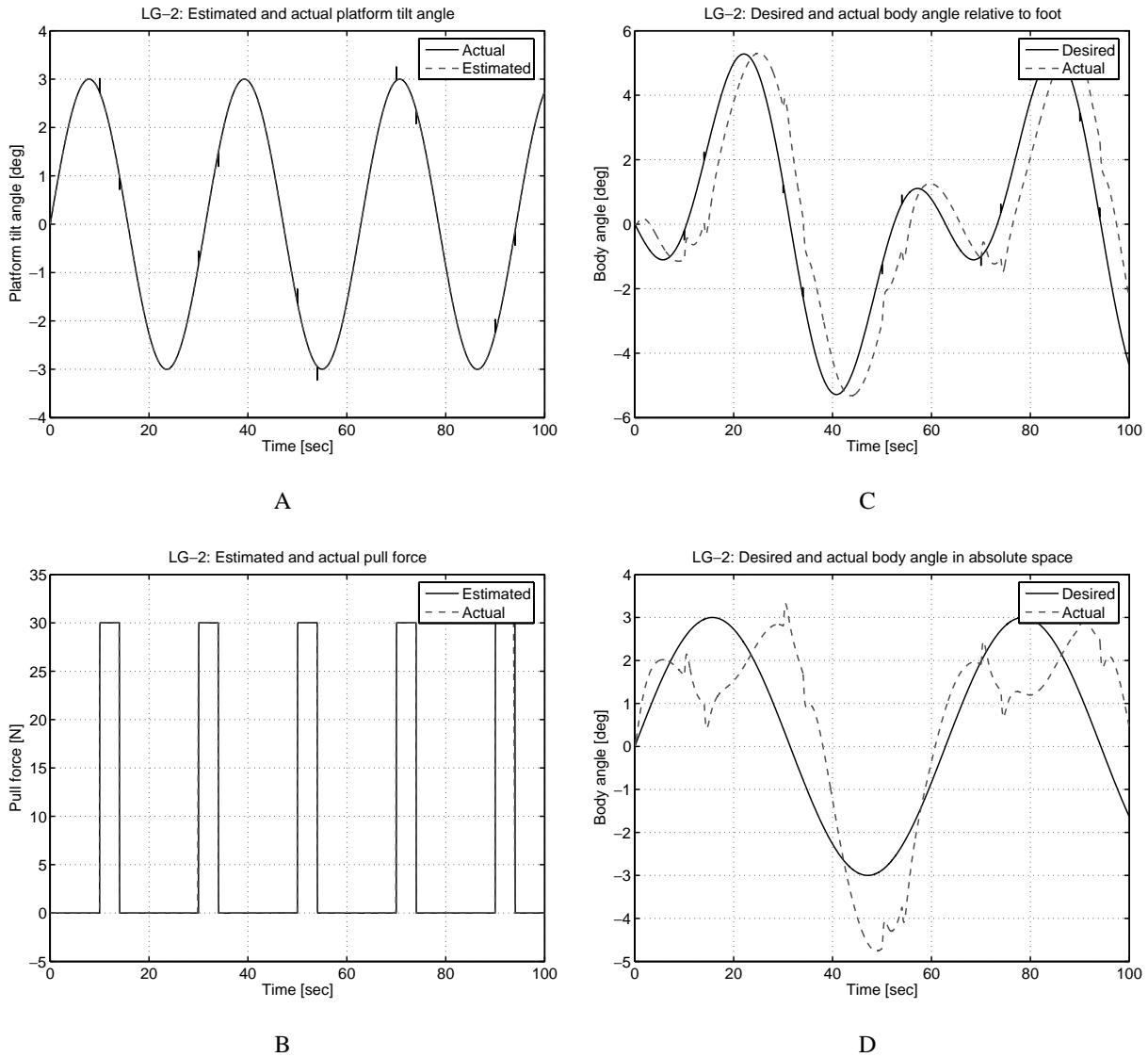


Fig. 7. Simulation results for the humanoid with voluntary motion and external pull force in the presence of platform tilt. The external disturbances are estimated by the means of an extended observer that estimates both the states and the disturbances based on the measurement of α , $\dot{\alpha}$, and a_x . Time delay of 100 millisecond is inserted between the controller and the actuator. The estimated and actual platform tilt angle is shown in (A); the estimated and actual external pull force is shown in (B); the desired and actual voluntary motion of the body relative to the foot is shown in (C); the desired and actual voluntary motion in absolute space is shown in (D).

ical findings and forge them in a formal frame with more possibilities for analysis and unified presentation; further it would introduce new concepts and techniques that can be beneficial for further exploration. On the other hand, neurological findings and knowledge in this closely-related-to-robotics field would open new horizons to interested engineers and would pose challenging question; answering such questions would open new research areas. Accordingly, the research results presented in this article serve the mentioned goals in

many ways:

1. A mutual interaction between engineering and biology is demonstrated by introducing a biocybernetics approach in Section 2 and by the means of devising PostuRob. PostuRob serves many purposes such as: A. To have a non-human testbed in order to avoid simulation limitations and simplifications. B. To test and to demonstrate the validity of the biological concepts. C. To propose a

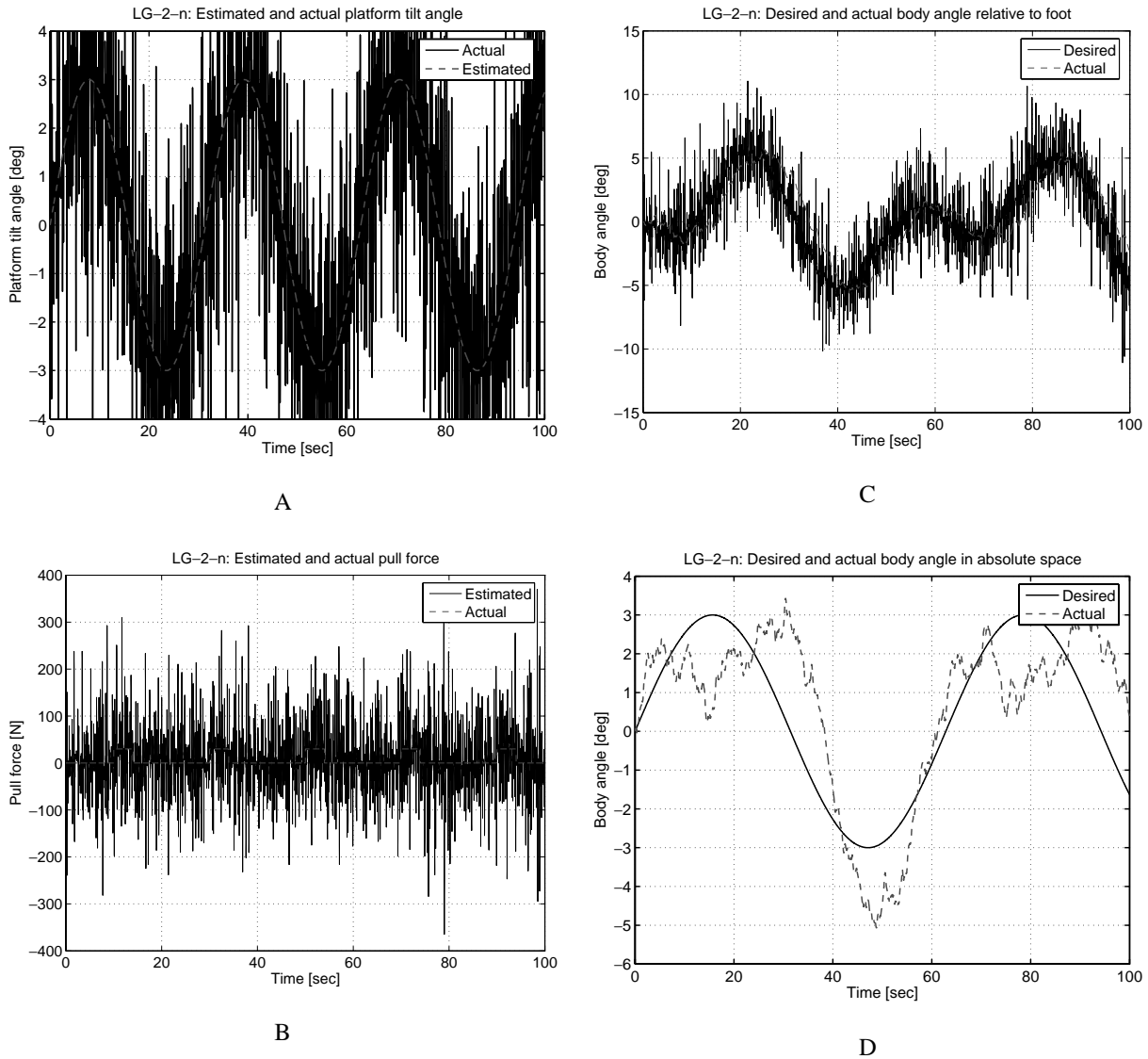


Fig. 8. Simulation results for the humanoid with voluntary motion and external pull force in the presence of platform tilt. The external disturbances are estimated by the means of an extended observer that estimates both the states and the disturbances based on the measurement of α , $\dot{\alpha}$, and a_x . Time delay of 100 millisecond is inserted between the controller and the actuator. Furthermore, random noise of about 10% of the signal magnitude is added to all sensor signals. The estimated and actual platform tilt angle is shown in (A); the estimated and actual external pull force is shown in (B); the desired and actual voluntary motion of the body relative to the foot is shown in (C); the desired and actual voluntary motion in absolute space is shown in (D).

novel approach to stance control of biped robots without much rigorous modeling and mathematical derivation; this approach is merely based on biological concepts.

2. The model-based methodology presented in the engineering section is based on neurological control frameworks lines such as its structure and main features (explicit estimation of external stimuli, compensation, PID control) while in-

heriting the same considerations and limitations (time delay, loop gains, stimuli superposition, sensor noise). The engineering architecture, though based on the neurological grounds, has its distinguished features and performance. This distinction is the sought byproduct of this interdisciplinary work which is hoped to incite more interaction and further exploration.

In summary, the common intended features of the two approaches are:

1. Both rely on the compensation of external disturbance effects.
2. Both employ a sort of PID controller.
3. Both assume the same realization of the time delay (lumped in one place).

To test the proposed engineering architecture, the special purpose humanoid "PostuRob" rather than the human body is considered. As a first attempt, only simulation results corresponding to the engineering approach are presented here. To this end, a dynamic model for the special-purpose humanoid is derived, an external-disturbance estimation method is presented, and finally a control method for compensating the estimated disturbances, stabilizing the system, and achieving desired voluntary motion is used. Here, the compensation of the estimated disturbances is based on direct torque compensation that is independent of the motion controller in the sense that it does not pass through the PID loop. Further, the PID controller is interpreted as a state-feedback controller (PD) and a integral internal model (I) tracking subsystem. Simulation results show the applicability of the presented method. From a pure engineering perspective, the following can be briefly stated:

1. Currently, it appears possible to use only one measurement (in addition to the foot-ankle measurements) for the purpose of estimating the disturbances and for controlling the motion.
2. It becomes necessary to use more measurements in the presence of sensor noise, especially if this considerably affects the force sensors.
3. It is more beneficial in the engineering approach to use the foot-platform tangential contact force (friction force) for the estimation process, rather than the sum of the vertical ones.
4. A linear controller can be used if the external disturbances are estimated and compensated for.
5. Frequency responses (phase and magnitude) depend on the controller gains and on the time delay assumed.

Carefully comparing the neurological and the engineering approaches, the main emerging differences can be stated as:

1. The compensation of the external disturbance effects is achieved by 'direct compensation' in the engineering approach, while it is achieved by means of a position compensation in the neurological approach.

2. The PID controller in the engineering approach does not deal with the disturbance compensation while it does so in the neurological approach, since there the equivalent position error passes through the PID controller.
3. The feedback loop is closed around the body-foot motion in the engineering approach while it is closed around the body-space motion in the neurological approach.
4. Only the states are fed back through the PD controller in the engineering approach chosen, while the tracking error is fed back through the PD controller in the neurological approach.
5. The estimation of external disturbances is based on a systematic full dynamic multi-input-multi-output model in the engineering approach while it is based on an ad-hoc simplest-possible solution approach that was governed by the biological knowledge and the cybernetic approach described.
6. No effort is made to filter sensor noise in the engineering approach where this is delegated to the extended observer, while a filtering effort is done on the individual signal level depending on knowledge about the biological sensors in the neurological approach.

Accordingly, it is claimed that this interdisciplinary study raises the following legitimate questions:

1. How well does the presented engineering method perform when applied to the real (robot) system?
2. What are the similarities and differences between the two presented models with respect to the real system?
3. What are the necessary steps or tools to transform one model into the other?
4. What are the effects of adding to the external disturbances support translation and having this explicitly estimated in distinction to the support rotation and the external pull force?
5. What would be the effect of adding low-frequency (similar to $1/f$) noise? If the vestibular system is used to discriminate between support tilt and translation, for instance, it involves the use of gyrometers, by which this kind of noise comes into play. This noise resembles in its frequencies closely the disturbance signals.
6. Which functional aspects would be covered by the engineering model and not by the neurological model? Can the engineering view suggest biological experiments which reveal the biological mechanisms in more depth?

Once these questions are answered, engineers can anticipate applying neurological knowledge in the field of human posture control to engineering application areas as humanoids. This may apply even to walking machines if one considers the possibility that external force stimuli (such as the pull on the body) are analogous to the dynamic force arising from body inertia during walking (eigen-inertia). On the other hand, biologists may find new ways of investigating, describing, and modeling human sensorimotor performance and may learn to understand it more in depth. This would not only be helpful for understanding sensorimotor impairments of neurological patients and the effects of successful therapies, but may be advantageous when it comes to construct and implement prostheses and exoskeletons. The fact that the sensorimotor control is based on biological concepts may increase patients' compliance to use them. Furthermore, the approach allows for a direct technical realization of medical sensorimotor aids.

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