P. Cisek, T. Drew & J.F. Kalaska (Eds.)
Progress in Brain Research, Vol. 165
ISSN 0079-6123

CHAPTER 18

Modeling sensorimotor control of human upright stance

Thomas Mergner*

Neurological University Clinic, Neurocenter, Breisacher Street 64, 79106 Freiburg, Germany

Abstract: We model human postural control of upright stance during external disturbances and voluntary lean. Our focus is on how data from various sensors are combined to estimate these disturbances. Whereas most current engineering models of multisensory estimation rely on "internal observers" and complex processing, we compute our estimates by simple sensor fusion mechanisms, i.e., weighted sums of sensory signals combined with thresholds. We show with simulations that this simple device mimics humanlike postural behavior in a wide range of situations and diseases. We have now embodied our mechanism in a biped humanoid robot to show that it works in the real world with complex, noisy, and imperfectly known sensors and effectors. On the other hand, we find that the more complex, internal-observer approach, when applied to bipedal posture, can also yield human-like behavior. We suggest that humans use both mechanisms: simple, fast sensor fusions with thresholding for automatic reactions (default mechanism), and more complex methods for voluntary movements. We suggest also that the fusion with thresholding mechanisms are optimized during phylogenesis but are mainly hardwired in any one organism, whereas sensorimotor learning and optimization is mainly a domain of the internal observers.

Keywords: human; posture; sensor fusion; model; sensorimotor control; top-down approach; robot

Introduction

How can organisms control their behavior when their knowledge of themselves and the world is based on noisy, variable, imperfect sensors? We are studying this question in the context of the upright posture of humans, which is a prerequisite for most of their voluntary movements. Upright stance is subject to many disturbances, including gravity, Coriolis and centrifugal forces, the body's own inertia, pushes and pulls exerted from the outside, and motion of the support surface. In view of all these hazards, one might assume that postural control must be very complicated. But we have shown that human-like behavior can be achieved by remarkably simple mechanisms (Mergner et al., 2002, 2003, 2005; Maurer et al., 2006). Implemented in simulations and in a real, biped humanoid robot ("PostuRob"), these mechanisms mimic the behavior of healthy humans and neurological patients in a wide range of experiments.

The central question is how the brain combines data from multiple imperfect sensors to estimate the disturbances. Nowadays, the usual approach in engineering is to use "internal observers" and this method has been used also in engineering-inspired biological models (e.g., Oman, 1982; Borah et al., 1988; Merfeld et al., 1993; van der Kooij et al., 2001). To explain this point, we refer

---

*Corresponding author. Tel.: +49 (0) 761 2705313; Fax: +49 (0) 761 2705203; E-mail: mergner@uni-freiburg.de

DOI: 10.1016/S0079-6123(06)65018-8

to an experience one often makes during voluntary behavior. One has the intuitive notion that one compares expected and actually occurring sensory and motor effects and normally finds that they match. This notion was discussed by von Holst and Mittelstaedt (1950). In their "reafference principle," sensory input is decomposed into self-produced sensory input (reafferent input) and input stemming from external disturbances (exafferent) with the help of knowledge about one's own activity (efference copy). An internal observer makes a similar comparison. It uses an "internal model" of the body, its dynamics, etc., to simulate its behavior in parallel to the actual outside behavior. The difference between the simulated behavior and the actual (monitored by sensors) is iteratively minimized to yield the observer's best guess as to what is really going on. This kind of model is powerful and widely used in engineering. But in what follows we explore the capabilities of a much simpler mechanism, which computes its estimates by summing and weighting sensor signals and putting them through thresholds. The difference in establishing disturbances estimates between the simple sensor fusion concept and the "observer" concept is highlighted in Fig. 1.

There have been a number of earlier attempts to model human postural control by multisensory feedback models (Nashner, 1972; Johansson and Magnusson, 1991; Fitzpatrick et al., 1996). But it remained for Peterka (2002) to validate this approach by demonstrating a close correspondence between human experimental and model simulation data (he did not address, however, the modeling of experimentally observed response nonlinearities and sensory re-weightings). In these previous studies, one may still recognize the classical textbook concept of postural reflexes with essentially direct sensor-actuator couplings. An exception is the model of van der Kooij et al. (1999, 2001) that is based on the internal observer concept with Kalman filter for sensory re-weighting and noise minimization (but still feeds back sensor signals). In contrast, our approach ignores the reflex concept. Instead, it focuses in an "inverse" (top-down) approach on implementing intersensory interaction principles derived from perception studies into sensorimotor control.

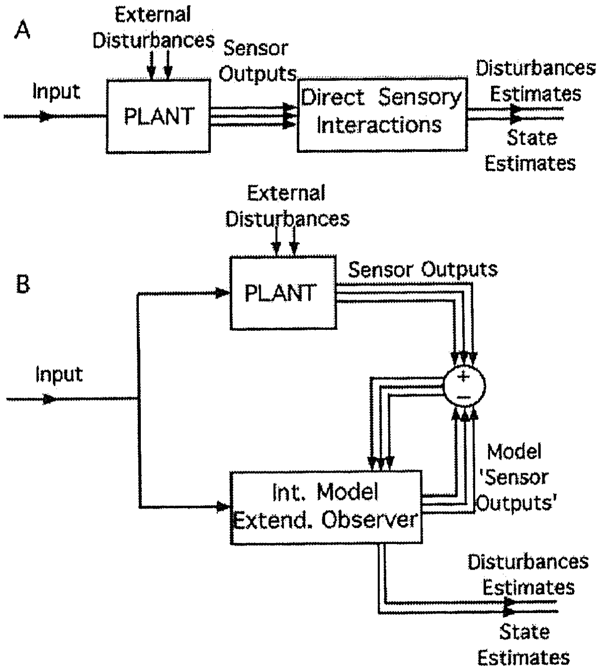

Fig. 1. Schematic presentation of two different concepts of how the brain may derive internal estimates of the external disturbances. (A) Simple "hardwired sensor fusion" concept. The estimates are obtained by direct (forward) intersensory interactions (i.e., without iterations). (B) "Observer" concept. An internal model of the body, its dynamics, etc., in the brain is used to "predict" sensor signals. They are compared to the actual sensor signals (delivered through the real body; Plant). The difference (error) is used in an iterative way to improve the predictions until it essentially becomes zero. Then the brain mechanism is able to deliver estimates of the external disturbances (Extended Observer) for use in sensorimotor control.

Sensors and sensory interaction principles in spatially oriented behavior

Physiological and clinical evidences indicate that humans use mainly *four different sensory inputs* for their spatially oriented behavior (e.g., Horak and Macpherson, 1996). In the following list, we include the technical sensors that are used by PostuRob.

(a) *Vestibular system — Inertial motion sensor.* The vestibular system measures 3D linear and angular body motion. It receives input from two receptor organs, the macular and semicircular canal organs. Both are encapsulated deep within the bone of the skull and thus are advantageous over other force-sensitive receptors in that they are not directly affected by internal or external tissue deformation (by reaction forces). Processing in the brain is thought to yield neural estimates of three quantities: 3D body-in-space rotational velocity, 2D body angle with respect to the gravitational vector, and 3D body-in-space linear velocity (Mergner and Glasauer, 1999; Zupan et al., 2002). Technical equivalents for the macular and canal organs would be a 3D accelerometer and a 3D gyrometer, respectively. They were combined in PostuRob in a biologically inspired vestibular system (see below).

(b) *Joint angle proprioception/sensor*. The human sense of joint position and velocity stems mainly from stretch receptors in muscles. But it may also be influenced by skin and joint-capsule receptors. PostuRob's analog is a goniometer that delivers both position and velocity signals.

(c) *Joint torque proprioception/sensor*. Joint torque is measured by force receptors in the tendons of the muscles that actuate the joint (Duysens et al., 2000). Another source is receptors deep in the foot arch which measure center of pressure (COP) shifts or other aspects of ground reaction forces (compare van der Kooij et al., 2005). The evidence comes from human posture control studies (e.g., Maurer et al., 2000, 2001). In PostuRob the analogous organs were sensors in the insertions of the artificial muscles and a COP monitor measuring pressure on forefoot and heel.

(d) *Visual motion and orientation sensors*. Visual motion stimuli induce body-sway responses (e.g., Mergner et al., 2005). However, the contribution of visual cues to posture control is not a crucial one in the present context. We therefore do not consider it here.

In psychophysical work on human self-motion perception, we have disclosed a number of sensor fusion principles that have been summarized elsewhere (Mergner, 2002). The main finding is that humans combine sensory signals to estimate the external events that evoke the motion. For instance, subjects perceive a passive head rotation on a stationary trunk when signals from vestibular and neck proprioceptive inputs are equal and opposite. When vestibular signals are matched by equal and opposite signals from leg proprioceptors, subjects perceive a body rotation on stationary feet. When vestibular signals are not balanced by any proprioception, subjects perceive that their support surface is rotating (given that haptic cues are indicating contact with a surface).

In our psychophysical studies of vestibular-neck and vestibular-leg interaction in human self-motion perception in the horizontal rotational plane (Mergner et al., 1991, 1993), we used sinusoidal rotation stimuli and compared gain and phase curves of the vestibular responses with simulations of the canal afferents' transfer characteristics known from sensory physiology and the vestibulo-ocular reflex (VOR; showing some prolongation of time constant). We found that, in contrast to these, the gain of the perceptual response is affected by the magnitude of the stimulus, unlike the phase. Alternating between experimental and modeling approaches suggested a central mechanism with the effect of a velocity-detection threshold, whose existence and characteristics could be experimentally determined (see Mergner et al., 1991). The approach and model elements were subsequently extended to cover the neck proprioceptive stimulus and finally various combinations of the two stimuli, until all experimental data could be reproduced in simulations of a "simplest-possible" model. The modeling process also took into consideration certain constraints. For instance, care was taken that it could be applied to other body segments such as the legs (see above) and extended to more than two body segments ("modularity" constraint). Indeed, it could be used to construct a broad and general framework for intersensory interactions in human spatially oriented behavior (see Mergner, 2002). Some of them will be addressed below (e.g., an automatic sensory re-weighting with noise reduction).

Sensor fusions in the sensorimotor control model

As a first step to modeling postural control, we note that under most common conditions, the kinetic equations of the system can be simplified. Body sway is usually small ($<4°$), which allows a small-angle approximation, ANGLE≈sin(ANGLE). Excursions can be mimicked as occurring predominantly about just one joint, the ankle, so the geometry can be approximated by an "inverted pendulum."

Accordingly, we built our principles for sensor fusion into an inverted-pendulum model of human stance (Fig. 2; simulation software: Simulink, Matlab®). For simplicity, the model is restricted to the sagittal plane. Kinetic aspects are added (impacts of gravity and external contact forces). Fusion-derived estimates of external disturbances are fed into the feedback loop together with a "voluntary lean" set point signal (assuming that volition normally deals with the body's orientation in space). The difference between feedback and set point is fed into a PID controller (P, proportional, I, integrative, and D, differential factors) to produce ankle joint torque by means of actuators (here taken to be ideal; we conceived that mechanisms in the human spinal cord account for non-optimal actuator characteristics such as nonlinearities and establish a single controller mechanism to simplify and unify feedback signals

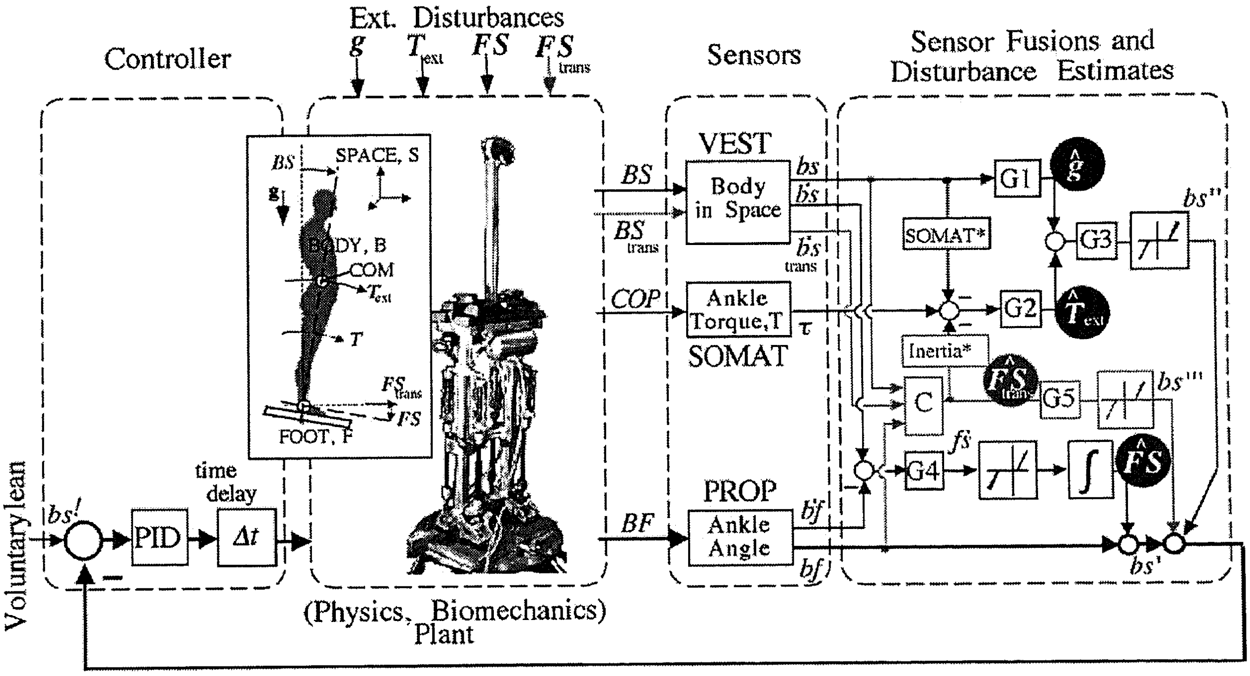

Fig. 2. Model of human posture control in sagittal plane. The model was derived from experimental data in humans and describes these in the form of a sensory feedback stabilization of an inverted pendulum (inset). Its sensorimotor control modules (boxes "Sensor Fusions and Disturbance Estimates" and "Controller") were furthermore used to control a biped humanoid robot (PostuRob; box Plant), where for the sensors (box Sensors) and actuators (not shown) corresponding "biologically inspired" technical devices were used. There are two main principles of the control. First, "*hardwired*" *sensor fusions* (intersensory interactions) yield *internal estimates* of the *external disturbances* (i.e., $\hat{g}$ for gravitational vector g, $\hat{T}_{ext}$ for external contact force T_{ext}, and $\hat{FS}$ for foot-space angle FS upon support-surface tilt; highlighted in circles). In this article we complete the model by adding the fourth external disturbance and its estimate ($\hat{FS}_{trans}$ for foot-space translation FS_{trans} upon support-surface translation; gray lines and symbols). The second main principle is that the estimates, after giving them a body-space angle dimension (bs', bs'', bs'''), are acting in a local proprioceptive feedback loop (bold lines) that receives a body-space angle "Voluntary lean" signal ($bs^!$) as set point signal. This yields an "*internal feed forward disturbance compensation.*" Sensors (transfer characteristics omitted): VEST, vestibular sensor, transforming "Body-Space" angle BS into corresponding angular position and velocity signals, bs and $\dot{b}s$ ("Body-Space" translation BS_{trans} into $\dot{b}s_{trans}$); SOMAT, yielding from somatosensory force receptors in the foot, a measure of center of pressure shift, COP, and transforming it into a measure of ankle torque τ; PROP, ankle angle sensor providing measures of body-foot angle and its velocity, bf and $\dot{b}f$. G1–G5, gain and transforming factors (further details in text).

and supra-spinal control signals from many different sources). As evaluated in a number of experiments in humans, it describes normal subjects' and vestibular loss patients' postural responses during various external disturbances (Mergner et al., 2003, 2005; Maurer et al., 2006). For instance, it describes the response gain and phase curves in Bode diagrams obtained during platform tilts and pull stimuli, both with and without body-sway referencing of the platform. It is also the control mechanism used in PostuRob (Mergner et al., 2006).

The main control principle is that the external disturbances are compensated for by (i) creating internal estimates of each disturbance, and (ii) feeding these estimates into a "local" body-foot (*bf*) proprioceptive feedback loop ("local loop," bold lines in Fig. 2). Kinetic disturbances are gravity, g, and external force, T_{ext}. Kinematic disturbances are a change in foot-space angle, *FS*, generated by support-surface tilt about the ankle joint, and translation of the foot in space at the ankle joint, FS_{trans}, upon support-surface translation. Before feeding the estimates into the feedback loop, they are referred to the same coordinates as the set point signal (body orientation in space, bs', in °). The feedback concept may be viewed as an "internal feed forward disturbance compensation". The loop gain per se, determined by the local proprioceptive loop, is very low (compare Fitzpatrick et al., 1996, who first reported a low-loop gain in postural control). But it increases to the extent that a given external disturbance has impact. The low-loop gain allows for considerable delay in the system (in the model, all delays are lumped together in one, 150 ms, taken from experimental data; Maurer et al., 2006).

Although the feedback loop combines both kinematic and kinetic estimates, a kinematic disturbance (e.g., support tilt) leads to a kinematic compensation, i.e., a change in body-foot angle that tends to keep the body upright in space. Correspondingly, a kinetic disturbance (e.g., external pull) leads to a kinetic compensation in terms of a corresponding counter torque in the ankle joint, while the body-space angle is maintained. (Note that the kinematic and kinetic parameters are linked to each other in the form that the body-space angle *BS* determines the gravitational ankle torque, T_{ank}, in the form of $T_{\text{ank}} = \mathrm{m} \times \mathrm{g} \times \mathrm{h} \times \sin(BS)$; m, body mass; h, height of m above ankle joint.) Conceivably, the performance of this simple control mechanism depends on the quality of the disturbance estimates (see below). Yet, there is redundancy in the system. Let us assume, for instance, that during an external force (pull) stimulus the ankle torque signal τ and thus the external force estimate $^{\wedge}T_{\text{ext}}$ is too low or too high, for some reason. This leads to an insufficient compensation, and this, in turn, to a body-space excursion with corresponding change of the gravitational ankle torque and its internal estimate ($^{\wedge}g$; derived from a vestibular signal of body-space angle, *bs*). Since $^{\wedge}g$ tends to reorient the body upright, it helps to cope with the $^{\wedge}T_{\text{ext}}$ error, so that balancing is nevertheless performed quite well. But the estimation errors remain.

The internal estimate of the support/foot tilt, $^{\wedge}FS$, in the model is derived from a combination of a vestibular body-space velocity signal and a proprioceptive body-foot velocity signal (via gain factor, velocity threshold, and mathematical integration). Since we are dealing here with signals of coplanar rotations, their combination is by simple vector summation, while in the 3D case it would require a coordinate transformation (see Mergner et al., 1997). This sensor fusion entails an automatic *sensory re-weighting* with two interesting aspects. This is explained using an enlarged section of the model (Fig. 3). There, the proprioceptive sensor measures body-foot position and velocity (bf, $b^{\cdot}f$). The vestibular sensor, upon body-space acceleration (second derivative, δ δ, of *BS*) delivers, after an acceleration-to-velocity integration (integration symbol), a measure of body-space velocity ($b^{\cdot}s$). It is assumed that this vestibular signal is very noisy and that the integration accentuates its low-frequency components. In contrast, noise in the bf and $b^{\cdot}f$ signals is considered to be small. In the subsequent central processing, the $b^{\cdot}f$ and $b^{\cdot}s$ signals are summed ($f^{\cdot}s = b^{\cdot}s - b^{\cdot}f$) and passed through a velocity threshold that is slightly larger than the vestibular noise, before an integration yields the estimate of foot-space tilt, $^{\wedge}FS$. Combining the estimate then with the proprioceptive bf signal yields a bs' signal

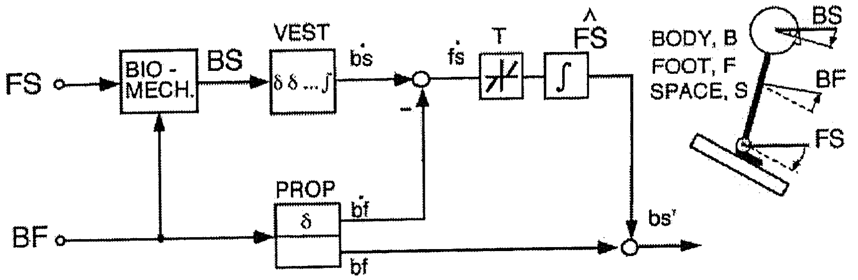

Fig. 3. Automatic sensory re-weighting mechanism (detail from model in Fig. 1; same abbreviations). The body-space output signal *bs*′, which is used for the feedback, results from combining the foot-space angle estimate $\hat{FS}$ with the body-foot angle signal *bf* (by which the local body-foot control becomes upgraded into a body-space control). This mechanism yields that *bs*′ is determined by proprioception (*bf*) when the support surface is stationary (since with $FS = 0^\circ$ also $\hat{FS}$ becomes 0°), while *bs*′ becomes mainly determined by the vestibular signal $\dot{b}s$ during support tilt (since the $\dot{b}f$ and *bf* contributions to *bs*′ then tend to cancel each other). Furthermore, with the vestibular signal $\dot{b}s$ carrying large noise and the proprioceptive signals small noise, the threshold (*T*; in the order of the vestibular noise) yields that the *bs*′ signal shows small noise with stationary support and large noise with tilting support. Note that *T* is a velocity threshold and therefore especially effective in reducing low-frequency noise contributions to *bs*′.

(used for the feedback). Note that this *bs*′ signal is determined solely by the low-noise proprioceptive input *bf* during body motion on stationary support (since $\hat{FS} = 0^\circ$; note that support stationarity corresponds to the most common behavioral situation). The *bs*′ signal involves the noisy vestibular signal only to the extent that there occurs a support tilt. The effect can be viewed as a noise "optimization".

To appreciate the other aspect of the sensory re-weighting in Fig. 3, let us start with the general consideration that a proprioceptive dominated *bs*′ signal would be appropriate only with stationary support; since it tends to align the body with respect to the support rather than in space, it would be inappropriate with support tilt. In contrast, a vestibular derived *bs*′ feedback signal would be appropriate with either stationary or tilting support, because it always tries to orient the body upright. The sensory re-weighting mechanism in Fig. 3 accounts for this by making the signal *bs*′ proprioceptive-determined whenever the support is stationary ($bs' = bf$; $\hat{FS} = 0^\circ$), and it makes it more and more vestibular-determined with increasing support tilt ($bs' \approx \int \dot{b}s$). Note from Fig. 3 that the threshold plays an important role in the sensory re-weighting. The thresholds in Fig. 2 were originally introduced to account for considerable amplitude nonlinearities of the stimulus responses (note that they are clearly lower than in the self-motion perception). For a quantitative assessment of their sensory re-weighting effects in humans upon changes in the external stimulus conditions, see Maurer et al. (2006).

In order to stress once more the robustness of the control, we refer to the estimate of the external contact force in Fig. 2, $\hat{T}_{\text{ext}}$, which is extracted from a measure of ankle torque, τ (here derived from foot-force receptors and the measure of COP shift; see above). The estimate is obtained by decomposing τ into its constituents, removing from it with the help of vestibular signals the dynamic and static torque components that arise with body excursions (box "Somat*;" see Maurer et al., 2006, for details). $\hat{T}_{\text{ext}}$ is then summed with the other kinetic estimate $\hat{g}$ and transformed by a factor (G3) into a kinematic equivalent, *bs*″. Above, we have considered that $\hat{g}$ helps to cope with errors of $\hat{T}_{\text{ext}}$. Here we consider the reverse, which is also true. The signal *bs*″ receives a contribution from the vestibular *bs* signal not only via $\hat{g}$, but also via the box "Somat*," yet with sign reversal, so that both essentially cancel each other out. Therefore, balancing on stationary support is not affected considerably by an inaccurate vestibular signal. Also upon complete loss of the vestibular sensor, where the signal paths via G1, box "Somat*," and G4 and G5 are set to zero (by some still-to-be-defined mechanisms in the patients), balancing on stationary support is not impaired. In contrast, balancing on tilting support is clearly affected (in the absence of vision), and in a way that is predicted by the model (Maurer et al., 2000, 2006).

In previous versions of the model, support translation as an external disturbance was not included. Yet, the previous model does compensate for this stimulus to the extent that it generates an ankle torque that tends to compensate inertial torque. In this form, however, it does not provide an estimate of the translation stimulus, but rather produces an error of the external force estimate. In the model of Fig. 2, we now have included a foot/support translation (FS_{trans}) and its internal estimate ($\hat{}FS_{\text{trans}}$), shown as gray print. The estimation is derived from vestibular signals of body-space translatory velocity and body-space angle, a body-foot angle proprioceptive signal, and known parameters (such as height of vestibular system and center of mass (COM) above joint, etc.; box "C"), and is taken to correct the external torque estimate (via box "Inertia*").

Embodiment of control principles into humanoid

The simple model of Fig. 2, conceivably, does not account for all currently known experimental findings in the human posture control literature, but does account for the types of sensors involved, the major aspects of the sensor fusions, and the control principles. To test this notion, the model was implemented into PostuRob, while making actuator performance essentially ideal. The robot's hardware (Fig. 2, box "Plant") consists of an aluminum frame with two feet, two rigid legs fixed to a pelvic girdle, and a spine, with the main "body" mass being represented by lead weights on the pelvis. It is freely standing on a motion platform that can be tilted or translated about the ankle joints. Each leg carries a front and back pneumatic "muscle" with "tendon" (spring) to move the body with respect to the foot and its support about the "ankle joint". To realize our notion of essentially "ideal actuators", we control the muscle-tendon system using tendon force feedback. The above-described sensors were implemented using appropriate electronics. The boxes "Sensor Fusions and Disturbance Estimates" and "Controller" in Fig. 2 were implemented in a Simulink version on an embedded PC under the control of a host PC. (Further technical specifications are given under www.uniklinik-freiburg.de/neurologie/live/forschung/sensorfusion/PostuRob.html.)

PostuRob was presented with the same experiments as in humans using similar PID factors. It is able to perform "voluntary" body lean movements while, at the same time, support tilt and external force stimuli are applied ("superposition criterion" of Mergner, 2004). Furthermore, it copes with compliant support surface (i.e., standing on foam rubber) and body sway referenced platform by which the proprioceptive feedback loop is opened (compare Maurer et al., 2006). Gain and phase curves of the postural responses closely mimic those of humans (i.e., with some under-compensation; see Tahboub and Mergner, 2007). The robot shows a low-loop gain that allows for delays well above 100 ms and makes the control very "soft" and compliant. Inaccurate sensor and control signals remain without major degradation of performance.

Thus, PostuRob's control architecture with "disturbance compensation" yields a robust and human-like performance. This may well be of interest for engineers who construct multipurpose humanoid robots (a "bionics" aspect). Furthermore, the explicit representation of the disturbances estimates create a meta-level that would allow PostuRob to communicate its knowledge about the outside world with other robots, or to store this information, etc. Future developments of PostuRob will focus on further and alternative control features, additional sensory re-weighting mechanisms, and on the modularity of the system by adding further body segments.

The work with PostuRob alerted us to a number of interesting aspects that did not per se arise from the computer simulations (for instance, unforeseen nonideal sensor performance, signal noise, offsets, drifts, etc., all often slightly changing "spontaneously" over time). Furthermore, we conceive that PostuRob's human-like performance will allow us to use it for developing neurological diagnostic and therapeutic tools using it in a hardware-in-the-loop simulation approach (see Mergner et al., 2006). Furthermore, the approach allows for a direct technical realization of medical sensorimotor aids such as protheses and exoskeletons. The biological background of the control principles likely increases the chance to win patients' compliance.

The fact that PostuRob's simple control concept (based on "hardwired" sensor fusions) differs considerably from contemporary engineering approaches ("observer" concept; see Introduction) led us to compare the two approaches.

Control engineering approach

In collaboration with a colleague from the robotics field, we started a closer inspection and analysis of PostuRob's structure and control architecture and parameters using mathematical models and modern control theory techniques (Tahboub and Mergner, 2007). We designed a state and disturbance estimator and a controller that allows voluntary motion in the presence of the above mentioned external disturbances (support tilt, pull). The goal is again to create a humanlike stance performance. Thus, PostuRob serves as a linkage between the robotics and the biological approach. To ease comparison, the main features of the biological control structure were used for the modeling framework: the architecture was structured as a combination of a tracking controller, sensor fusions, disturbance estimations, and disturbance compensation. However, instead of using the "inverted-pendulum" simplification, we modeled the humanoid fully with its two rigid bodies. The same sensors as before were available. Furthermore, we took into account the friction (or shear) force between the foot and the platform, which we also measured.

For the model, equations of motion were linearized and expressed in state-space form. Geometric and mass parameters were identified and measured in experiments which comprised inclinations of the robot's body and/or tilts of the platform with known angles (1–4°), while measuring platform normal forces and applied torques. The mass moment of inertia was approximated. For the estimation of the external disturbances, measures of body-foot angle (and angular velocity), body acceleration at a known point, and reaction forces were obtained. Using a linearized dynamics model, the estimation was performed by the means of an extended observer (which later may ease application of these methods to higher dimensional systems including more body segments and more degrees of freedom). Thus, in addition to the use of the regular states body-foot angle and its velocity, the support tilt angle and the external pull force were taken as the third and fourth states. Since the latter states are extraneous to the system, a solution with quasi static linear state-space representation was chosen and observability was proven. A set of full-order observers were tested, with the difference between the real measurements and the observer-generated measurements being fed back to force the estimation error to converge to zero.

The control strategy was geared to that of a PID controller as before. However, a different interpretation was given to this controller. It was 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. The closed-loop feedback gains were chosen such that they were similar to those identified in human control.

For the simulations (in a Simulink environment), the eigenvalues of the extended estimator were chosen to be faster than those of the closed-loop controlled system to guaranty "real-time" estimation convergence. The same eigenvalues were used for a set of observers using different measurements. Stability and convergence were demonstrated in all experiments even in the presence of measurement noise and a 100 ms time delay. Employing, in addition to the body-foot angle and angular velocity, measures of the normal force, shear force, or acceleration yielded essentially similar estimation results and similar tracking errors for voluntary motion. Employing all measures at the same time did not improve the estimation considerably. However, when white noise was added (10% of signal amplitude), the use of all measures did yield a clear improvement.

In the robot, the "engineering" control yielded qualitatively similar responses as before the "biological" one (preliminary results). Before reaching detailed conclusions, however, we have to await further extensive testing. An interesting, though preliminary, finding was that the use of PostuRob's artificial vestibular system considerably improves its control, especially if the disturbances include support translation. This sensor system provides measures of body-space angle, angular velocity, and translatory velocity, derived by means of a sensor fusion of gyrometer and accelerometer signals (see above, Sensors). In the following discussion we present some "biologically inspired" steps in the development of the technical sensor system, which vice versa inspired interesting inferences on the biological sensor.

Artificial vestibular system

In higher animals and man, the oculomotor system and the skelotomotor postural system show spontaneous movements in terms of slow fluctuations (low-frequency noise), which appear to stem mainly from vestibular input. In the absence of visual stabilization, the eyes show slow spontaneous drifts. Also the body shows spontaneous sway with a low-frequency preponderance (Carpenter et al., 2001). Furthermore, the aforementioned vestibular self-motion perception shows considerable slow variations over time, unlike its proprioceptive counterpart (Mergner et al., 2001). This perceptual phenomenon is particular in so far that the variability is observed only during motion, whereas rest (i.e., stationarity of the body) is associated with subjective stability of the self and surroundings. We had explained this stability by a relatively high central velocity threshold in the vestibular perception (Mergner et al., 1991). We postulated that the threshold copes for an increase of low-frequency noise of the canal afferent signal, which results from a central prolongation of the time constant (from $T \approx 5$ s to $T \approx 20$ s). When designing PostuRob's artificial vestibular system, we reconsidered this problem.

With angular acceleration as input to a gyrometer (or to a vestibular canal system) and with a further processing of the gyrometer's angular velocity signal to yield angular displacement as output for control purposes, one has overall two integrations (in the mathematical sense). The first (acceleration-to-velocity integration) in the sensor is mechanical (in the canals considered to be "leaky" with 5 s time constant). Theoretically, at least, noise arising at the input site somewhere before the integration is transformed into a $1/f$ noise (meaning that noise amplitude increases, the lower the frequency is). The second integration (velocity-to-position) transforms this then into $1/f^2$ noise, and it transforms the noise that arises after the first integration into $1/f$ noise. Low-frequency noise is especially detrimental to function, because the motor behavior occurs mainly in the mid- to low-frequency range. How to deal with this problem? In the engineering field, one performs traditionally a high-pass filtering of the gyrometer signal. Our "biologically inspired" approach is similar, but goes beyond it.

In PostuRob's artificial vestibular system, the gyrometer output at rest shows noise with a clear preponderance at low frequency, albeit not exactly with a $1/f$ characteristics (Fig. 4A; $1/f^2$ in power spectrum histograms). The low-frequency preponderance becomes stronger after the velocity-to-position integration (Fig. 4B, 1). The latter signal showed very slow drifts that were eliminated by high-pass filtering the gyrometer signal with a 100 s time constant (which is in the order of the vestibular adaptation time constant) (Fig. 4B, 2). When further adding after this a high-pass filtering with $T = 5$ s (to mimic the "leak" in the canal's acceleration-to-velocity integration), a pronounced further reduction in noise resulted (Fig. 4B, 3). Introducing finally a velocity threshold led to still further noise reduction (Fig. 4B, 4).

Conceivably, a gyrometer response to a 0.2 Hz rotation stimulus is not affected considerably by these procedures (apart from a slight reduction through the velocity threshold). In contrast, a response at 0.02 Hz would be clearly affected. This was accounted for concerning the vertical planes by a sensor fusion with accelerometer signals, which provided the missing low frequency response components. The method we used is based again simply on a "hardwired" fusion (described elsewhere; Mergner and Glasauer, 1999). The fusion also decomposes gravitational and translational (inertial) components of the accelerometer

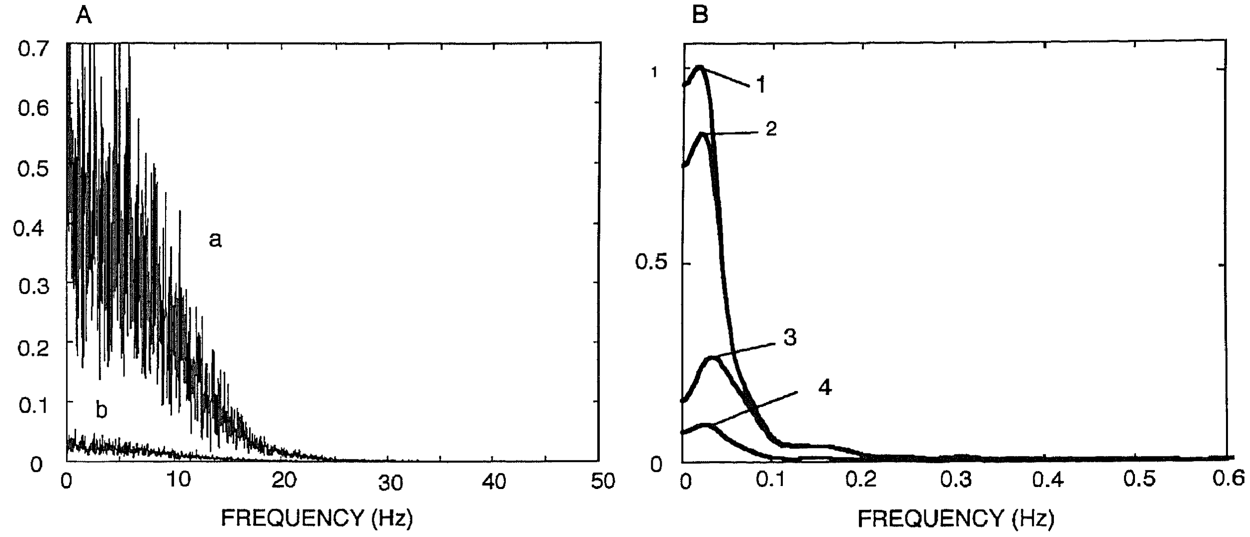

Fig. 4. "Biologically inspired" noise reduction of gyrometer readings (taken to represent vestibular canal signals) for PostuRob's artificial vestibular system. Plots of power spectrum histograms, PSH, of 400 s time series. (A) Superposition of PSP derived from one gyrometer signal (a) (ADXRS401, Analog Devices) and of a PSP derived from averaging 16 gyrometer signals (b). Note the low-frequency preponderance of the noise, presumed to be related to the acceleration-to-velocity integration of the sensor's operation. The clear reduction of the low-frequency noise by the averaging demonstrates that the noise sources were essentially independent of each other. (B) Effect of subjecting the averaged gyrometer signal to a velocity-to-position integration (1) and introducing, in addition, an adaptation time constant (2; high-pass filtering, $T = 100$ s, which is similar to the human canal adaptation time constant) which entails some noise reduction. More noise reduction is obtained by adding a further high-pass filtering, mimicking the "leak" in the acceleration-to-velocity integration with $T = 5$ s (3) and a velocity threshold (4; 0.5°/s). We conceive that nature uses such a bundle of "hardwired" noise reduction measures for the use of the canal signal in a canal-otolith sensor fusion (see text).

signals. Overall, it yields the bs, b^*s, and b^*s_{trans} signals shown in Fig. 2. Noticeably, there are comparable canal-otolith interaction models in the literature, but again these use or build upon the iterative "observer" concepts inspired by contemporary engineering methods (Merfeld et al., 1993; Zupan et al., 2002).

Discussion

In our "inverse" approach, we evaluated sensorimotor control of human spatially oriented behavior in a "top-down" rather than in a "bottom-up" way. We proceeded from the general notion that, in the metaphor of "the whole and its elements," different ways of combining the elements in a synthetic way would be possible, with differing results as to the quality of the whole (meaning here behavior). However, as long as the quality of the whole is not defined, the choice of the bottom-up synthetic way is arbitrary. To overcome this problem, we first performed behavioral experiments and studied the interaction between sensory signals. As already mentioned, we proceeded from the assumption that, within the sensorimotor framework chosen, the motor aspects are correctly performed.

One could object to this approach because the choice of the synthetic way is not arbitrary as, actually, demonstrated by our studies. They show that the disclosed sensor fusion mechanisms reconstruct the external physics. The internal estimates of the external disturbances are then used to neutralize the disturbances and this allows for undisturbed volition. From this viewpoint, the solution represents the most straight-forward way of dealing with sensorimotor control and thus is trivial. However, as described elsewhere (Mergner, 2002), the internal reconstruction of the physics is not necessarily straightforward. For instance, vestibular information that is used in a retrospective spatial arm-pointing task is not directly transformed from head via trunk to arm coordinates, but the transformation is via an estimate of the kinematics of the body support surface (Mergner et al., 2001).

Furthermore, this objection represents a post hoc view and does not acknowledge the novelty of the present concept as compared to the postural reflex concept in current textbooks where the sensor signals are coupled directly to the motor system instead of using them for disturbance estimation (compare Mergner, 2004). And this view does not consider the problem that arises from information loss due to non-ideal sensors and from noise, drifts, etc. It is mainly this problem that led engineers to establish elaborate mechanisms that can deal with inaccurate and changing sensory information. These include the aforementioned iterative "observer concept" (see Introduction). The fact that also the simple "hardwired sensor fusion" concept successfully deals with the problem (by way of the described "automatic sensory re-weighting with noise optimization") is certainly not trivial. The problem is dealt with, again in a "hardwired" way, already at the level of the sensors (see above, Artificial vestibular sensor).

Similarly, the use of the disturbance estimates for an "internal feed forward disturbance compensation" (by feeding them into the local proprioceptive feedback loop) is not straightforward. This implementation creates a number of noteworthy features. One consequence, for instance, is that loop gain is low, thus allowing for considerable feedback delay. Because of this, PostuRob shows a soft and humanlike response "behavior." Furthermore, the resulting network yielded the described remarkable robustness of the control (and, as to be shown in the future, eases modularity of the concept). Finally, future applications of the concept may profit from the fact that the disturbance estimates provide a meta-level for communicating or storing the robot's estimates about the outside world and, vice versa, at this level stored or communicated knowledge can be fed into the control for correcting or improving the estimates.

Another objection could be that the simple "hardwired sensor fusion" control is actually the result of our modeling attempt to simplify the model as far as possible (following "Occam's razor" rule; Gibbs and Sugihara, 1996/1997) rather than of a simplification performed by nature during phylogenesis. Therefore, one cannot exclude that the mechanism actually is more complex (which, indeed, is true). For instance, one could conceive that the same functionality is achieved with control mechanisms that extract the disturbance estimates by way of the "observer concept." It has been shown that such models can describe different types of sensorimotor control and that, with certain extensions, they show adaptive properties, which is one of the most outstanding features of brain function (Tin and Poon, 2005). A postural control model of this kind with adaptive Kalman filter for sensory re-weighting and noise minimization has, indeed, been suggested by van der Kooij et al. (2001), as we mentioned before.

However, since we have not investigated adaptation in our experimental studies and have no data from which we might derive its rules, we should not include it into our model. Yet, we conceive that adaptive properties play an important role, together with cognitive mechanisms that have been shown to also contribute to posture control (e.g., Blumle et al., 2006). We like to point out, however, that the "hardwired sensor fusion" model would be prepared to incorporate adaptive and cognitive mechanisms (via the internal estimates as interface or further sensory re-weighting mechanisms).

It also contains internal models (internal representations) of the outside world and the body, some of which have to be parameterized and can be adjusted. These models relate, however, solely to the information pick-up by the sensors (e.g., the topology of the wiring relates to the way in which the physical stimuli interact, and certain parameters account for body mass, gravity, etc.) and are not used to internally create a "virtual body motion" as in the "observer" concept.

We see in the above described "hardwired sensor fusion" concept a simple, fast, and non-iterative alternative to the "observer" concept. It is possible that the latter shows advantages as concerns mathematical treatment and engineering applicability (this appears to relate primarily to research and not to praxis, however). Yet, these aspects tell nothing about the biological plausibility. We try to resolve this confrontation in terms of two alternatives by hypothesizing their coexistence. In this framework, the simple "hardwired" concept would represent the fast, basic mechanism (optimized during phylogenesis and possibly already "pre-wired" at birth), on which a more complex "observer" concept is superimposed. A fawn, for example, might use the basic simple mechanism for posture control when forced to flee shortly after birth (i.e., before it could learn much). The adult individual may still automatically resort to this as a default mechanism in response to unforeseen external disturbances. The superimposed "observer" mechanism, in contrast, might be used mainly during voluntary ("proactive") movements for learning and optimization and not so much during compensatory ("reactive") movements that aim to maintain posture and are more stereotype.

This framework might explain certain differences between the "proactive" and "reactive" types of movements described in the literature. For example, the control of a voluntary targeting of the eyes or the head in space tends to be restricted to two degrees of freedom, which may be learned in order to minimize computational effort, for instance, whereas 3D external disturbances of these movements are compensated for in 3D (compare Tweed, 2003).

It is to say, however, that evidence for the "efference copy" (EC) concept, at least so far, is primarily related to the oculomotor system. There, for some unknown reasons, kinematic and kinetic proprioception appears to contribute little to ongoing sensorimotor control, so that most researchers use in modeling an EC signal in substitution for the proprioceptive eye-head position or velocity signal. Otherwise, there is not much evidence for the EC concept in sensorimotor control, to my knowledge. Reported evidence relates mainly to higher levels of brain function that include perception, such as in the aforementioned intuitive example where we said that one tends to compare expected and actually occurring sensory inputs.

The simple "hardwired" concept has had its "baptism of fire" already. When we "embodied" it into PostuRob, we found that it works and that the robot shows the expected humanlike response behavior. It is robust against noise, signal drifts, etc., and fulfils the aforementioned "superposition criteria" when combining different stimuli and volitional lean. We conceive that its medical use in the form of "hardware-in-the-loop simulations" may help to better understand normal stance control, its impairment in patients, and the effects of therapies and may help to design new therapies and medical sensorimotor aids (see Mergner et al., 2006). Furthermore, it may give inspirations to colleagues from the robotics field (where the engineering attempts to create humanlike biped walking have not been very successful, to date). The embodiment of the "observer" concept into PostuRob still has to prove its validity. A preliminary finding is that it can do a similar job, but a detailed comparison is still missing. We expect from the comparison also considerable insights into presumed biological sensorimotor control concepts, which brings us back to our idea of an "inverse" approach (Introduction).

Given that both concepts turn out to be functionally equivalent in most respects, one may ask which is then the one that is used by humans for a given task. Waiting for evidence from electrophysiological and functional imaging research is, in the short term, not very promising. We speculate that some hint may be obtained from behavioral observations. Both the "hardwired sensor fusion" concept and the "observer" concept allow one to predict postural responses after loss of vestibular sensor function. The "observer" concept, as currently realized in our approach at least, would predict little functional impairment. The prediction of the "hardwired sensor fusion" concept is similar for situations where the support surface is stationary. However, it predicts inadequate postural responses upon platform tilts (with eyes closed). This is in line with our experimental findings. Blindfolded vestibular loss patients, unlike normal subjects, fall with fast platform tilts in a way as predicted (Maurer et al., 2006). It therefore appears that non-vestibular graviceptive sensors, for instance visceral ones (Mittelstaedt, 1996) or force/torque related ones (see above), can make only a partial substitution (essentially static or low frequency). Thus, an elaborate iterative disturbance estimation is here apparently not performed, at least not to the extent that the disturbance responses become normal. This may depend, conceivably, on the currently available processing resources. Vestibular loss patients' ability to consciously detect and to correctly interpret horizontal body rotations is impaired as compared to intact subjects, and this clearly is more when they are involved in performing some task (Schweigart et al., 1993).

Last but not least, we discuss our observations made with the "biologically inspired" vestibular system. The situation here is essentially parallel to the above considerations, in that we realized a "hardwired sensor fusion" concept, while others favor corresponding "observer" concepts (Merfeld et al., 1993; Zupan et al., 2002). However, we like to focus here on a different aspect, which is our notion that an embodiment of the biological concepts into a simple technical device may have an impact on our understanding of these concepts. We considered that a gyrometer is, at least to some extent, an equivalent to the vestibular canal system. We mimicked the "leak" of the acceleration-to-velocity integration ($T \approx 5\,\mathrm{s}$), known from the afferent canal signal, in the gyrometer signal (technically specified as having DC sensitivity) by applying a corresponding high-pass filtering. The measured noise of the gyrometer's velocity signal, which showed a clear low-frequency preponderance, was clearly reduced by this filtering, as especially evident in the corresponding angular displacement signal.

Our inference back for the biological sensor would be that the "leak" in the canal signal processing does not so much reflect a functional deficit, but rather a useful "noise reduction measure," similar as the other two "biological" steps we applied, i.e., the inclusion of an adaptation time constant and a velocity detection threshold. Future research may readdress this aspect in relation to the canal's geometry. The sensor has essentially not changed form and dimensions since its invention early in phylogenesis in fishes and across many species with vastly different body sizes. This feature was taken in a recent study (Squires, 2004) to ask whether the canal's dimensions reflect a design by nature for optimal sensitivity. Taking into account the basic building materials and physical and physiological operation constraints, the author calculated the optimal canal geometry and concludes that the result of his calculation corresponds largely to the biological realization. We would hold that such a consideration of the canal's optimal sensitivity should include the "leak" versus noise aspect.

In summary, implementation of simple sensor fusion principles derived from perception studies into a sensorimotor control model of human stance led to a powerful solution that could successfully be embodied into a humanoid robot and bears well comparison with much more complex engineering solutions. Our interplays between biological and engineering approaches yielded interesting and novel vistas from which both approaches profit. As a hypothesis for the future, we conceive that a simple and fast fusion-with-thresholding control coexists in parallel to a more complex observer-based control in humans. From this we like to suggest such a dual control also for humanoid robots, with a fast and essentially hardwired sensor fusion control (mostly passive, electronics-based) and a more complex and flexible software-based (active) control, such that the former takes over when the latter is too slow or fails.

Abbreviations

$BF/bf/b^{\bullet}f$	body-foot angle/internal proprioceptive signal of body-foot angle/velocity
bs^{l}	voluntary lean command signal (a body-space signal)
$BS/bs/b^{\bullet}s$	body-space angle/vestibular signal of body-space angle/velocity
$BS_{\mathrm{trans}}/b^{\bullet}s_{\mathrm{trans}}$	body-space translation/vestibular signal of body-space translatory velocity
COM	center of mass
COP	center of pressure
EC	efference copy

$FS/fs/\dot{f}s$	foot-space angle/internal signal of foot-space angle/velocity
$FS_{\mathrm{trans}}/\hat{}FS_{\mathrm{trans}}$	foot-space translation/internal estimate of it
$g/\hat{}g$	gravity/estimate of gravitational contribution to ankle torque
G1–G5	internal gain and transforming factors
PROP	proprioceptive sensor
SOMAT/“Somat*”	somatosensory sensor/internal model of it
$T_{\mathrm{ext}}/\hat{}T_{\mathrm{ext}}$	external force/internal estimate of it
τ	ankle torque signal
VEST	vestibular sensor
VOR	vestibulo-ocular reflex

Acknowledgments

Supported by DFG Me 715/5-3. I like to thank W. Becker and D. Tweed for helping me to improve the manuscript.

References

Blumle, A., Maurer, C., Schweigart, G. and Mergner, T. (2006) A cognitive intersensory interaction mechanism in human postural control. Exp. Brain Res., 173: 357–363.

Borah, J., Young, L.R. and Curry, R.E. (1988) Optimal estimator model for human spatial orientation. Ann. N.Y. Acad. Sci., 545: 51–73.

Carpenter, M.G., Frank, J.S., Winter, D.A. and Peysar, G.W. (2001) Sampling duration effects on centre of pressure summary measures. Gait Posture, 13: 35–40.

Duysens, J., Clarac, F. and Cruse, H. (2000) Load-regulating mechanisms in gait and posture: comparative aspects. Physiol. Rev., 80: 83–133.

Fitzpatrick, R., Burke, D. and Gandevia, S.C. (1996) Loop gain of reflexes controlling human standing measured with the use of postural and vestibular disturbances. J. Neurophysiol., 76: 3994–4008.

Gibbs, P. and Sugihara, H. (1996/1997) What is Occam's Razor? Usenet Physics FAQ, http://math.ucr.edu/home/baez/physics/General/occam.html

von Holst, E. and Mittelstaedt, H. (1950) Das Reafferenzprinzip (Wechselwirkungen zwischen Zentral nervensystem und Peripherie). Naturwissenschaften, 37: 464–476.

Horak, F.B. and Macpherson, J.M. (1996) Postural orientation and equilibrium. In: Rowell L. and Shepherd J. (Eds.), Handbook of Physiology I: Excercise, Regulation and Integration of Multiple Systems. Oxford University Press, New York, pp. 255–292.

Johansson, R. and Magnusson, M. (1991) Human postural dynamics. Biomed. Engin., 18: 413–437.

van der Kooij, H., van Asseldonk, E. and van der Helm, F.C.T. (2005) Comparison of different methods to identify and quantify balance control. J. Neurosci. Methods, 145: 175–203.

van der Kooij, H., Jacobs, R., Koopman, B. and Grootenboer, H. (1999) A multisensory integration model of human stance control. Biol. Cybern., 80: 299–308.

van der Kooij, H., Jacobs, R., Koopman, B. and van der Helm, F. (2001) An adaptive model of sensory integration in a dynamic environment applied to human stance control. Biol. Cybern., 84: 103–115.

Maurer, C., Mergner, T., Bolha, B. and Hlavacka, F. (2000) Vestibular, visual, and somatosenory contributions to human control of upright stance. Neurosci. Lett., 281: 99–102.

Maurer, C., Mergner, T., Bolha, B. and Hlavacka, F. (2001) Human balance control during cutaneous stimulation of the plantar soles. Neurosci. Lett., 302: 45–48.

Maurer, C., Mergner, T. and Peterka, R.J. (2006) Multisensory control of human upright stance. Exp. Brain Res., 171: 231–250.

Merfeld, D.M., Young, L., Oman, C. and Shelhamer, M. (1993) A multi-dimensional model of the effect of gravity on the spatial orientation of the monkey. J. Vestib. Res., 3: 141–161.

Mergner, T. (2002) The Matryoshka Dolls principle in human dynamic behavior in space: a theory of linked references for multisensory perception and control of action. Curr. Psychol. Cogn., 21: 129–212.

Mergner, T. (2004) Meta level concept versus classic reflex concept for the control of posture and movement (in honour of O. Pompeiano). Arch. Ital. Biol., 142: 175–198.

Mergner, T. and Glasauer, S. (1999) A simple model of vestibular canal-otolith signal fusion. Ann. N.Y. Acad. Sci., 871: 430–434.

Mergner, T., Hlavacka, F. and Schweigart, G. (1993) Interaction of vestibular and proprioceptive inputs. J. Vestib. Res., 3: 41–57.

Mergner, T., Huber, W. and Becker, W. (1997) Vestibular-neck interaction and transformations of sensory coordinates. J. Vestib. Res., 7: 119–135.

Mergner, T., Huethe, F., Maurer, C. and Ament, C. (2006) Human equilibrium control principles implemented into a biped robot. In: Zielinska, T. and Zielinski, C. (Eds.), Robot Design, Dynamics, and Control (Romansy 16, Proceedings of the sixteenth CISM-IFToMM symposium), CISM courses and lectures No. 487, Springer, Wien, NY, pp. 271–279.

Mergner, T., Maurer, C. and Peterka, R.J. (2002) Sensory contributions to the control of stance: a posture control model. Adv. Exp. Med. Biol., 508: 147–152.

Mergner, T., Maurer, C. and Peterka, R.J. (2003) A multisensory posture control model of human upright stance. Prog. Brain Res., 142: 189–201.

Mergner, T., Nasios, G., Maurer, C. and Becker, W. (2001) Visual object localization in space: interaction of retinal, eye position, vestibular and neck proprioceptive information. Exp. Brain Res., 141: 33–51.

Mergner, T., Schweigart, G., Maurer, C. and Blümle, A. (2005) Human postural responses to motion of real and virtual visual environments under different support base conditions. Exp. Brain Res., 167: 535–556.

Mergner, T., Siebold, C., Schweigart, G. and Becker, W. (1991) Human perception of horizontal head and trunk rotation in space during vestibular and neck stimulation. Exp. Brain Res., 85: 389–404.

Mittelstaedt, H. (1996) Somatic graviception. Biol. Psychol., 42: 53–74.

Nashner, L.M. (1972) Vestibular postural control model. Kybernetik, 10: 106–110.

Oman, C. (1982) A heuristic mathematical model for the dynamics of sensory conflict and motion sickness. Acta Otolaryngol. Suppl., 392: 1–44.

Peterka, R.J. (2002) Sensorimotor integration in human postural control. J. Neurophysiol., 88: 1097–1118.

Schweigart, G., Heimbrand, S., Mergner, T. and Becker, W. (1993) Role of neck input for the perception of horizontal head and trunk rotation in patients with loss of vestibular function. Exp. Brain Res., 95: 533–546.

Squires, T.M. (2004) Optimizing the vertebrate vestibular semicircular canal: could we balance any better? Phys. Rev. Lett., 93: 1981061–1981064.

Tahboub, K. and Mergner, T. (2007) Biological and engineering approaches to human postural control. Integrated Comput. Aided Engin., 14: 15–31.

Tin, C. and Poon, C.-S. (2005) Internal models in sensorimotor integration: perspectives from adaptive control theory. J. Neural Eng., 2: S147–S163.

Tweed, D. (2003) Microcosmos of the Brain: What Sensorimotor Systems Reveal about the Mind. Oxford University Press, Oxford, NY.

Zupan, L., Merfeld, D.M. and Darlot, C. (2002) Using sensory weighting to model the influence of canal, otolith and visual cues on spatial orientation and eye movements. Biol. Cybern., 86: 209–230.