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Is a "loss of balance" a control error signal anomaly? Evidence for three-sigma failure detection in young adults

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Abstract

Given that a physical definition for a loss of balance (LOB) is lacking, the hypothesis was tested that a LOB is actually a loss of effective control, as evidenced by a control error signal anomaly (CEA). A model-reference adaptive controller and failure-detection algorithm were used to represent central nervous system decision-making based on input and output signals obtained during a challenging whole-body planar balancing task. Control error was defined as the residual generated when the actual system output is compared with the predicted output of the simple first-order polynomial system model. A CEA was hypothesized to occur when the model-generated control error signal exceeded three standard deviations (3Σ) beyond the mean calculated across a 2-s trailing window. The primary hypothesis tested was that a CEA is indeed observable in 20 healthy young adults (ten women) performing the following experiment. Seated subjects were asked to balance a high-backed chair for as long as possible over its rear legs. Each subject performed ten trials. The ground reaction force under the dominant foot, which constituted the sole input to the system, was measured using a two-axis load cell. Angular acceleration of the chair represented the one degree-of-freedom system output. The results showed that the 3Σ algorithm detected a CEA in 94% of 197 trials. A secondary hypothesis was supported in that a CEA was followed in 93% of the trials by an observable compensatory response, occurring at least 100 ms later, and an average of 479 ms, later. Longer reaction times were associated with low velocities at CEA, and vice versa. It is noteworthy that this method of detecting CEA does not rely on an external positional or angular reference, or knowledge of the location of the system's center of mass.

Keywords: Balance; Control; Posture; Falls; Detection

1. Introduction

In any country and in any language, humans intuitively understand what is meant by a "loss of balance" (LOB). Yet, how and when the central nervous system (CNS) decides, in quantitative terms, that a LOB has occurred is not understood. The noun 'balance' is defined in the Oxford English Dictionary (OED) as 'that which balances, or produces equilibrium', and as 'stability or steadiness due to the equilibrium prevailing between all the forces of the system'. For slow, quasistatic movements, balance is said to be controlled when the projection of the center of mass (COM), usually the center of gravity (COG), is maintained within the base of support (BOS). In more rapid movements, work by Pai et al. has shown that, while rising from a chair, balance can also be controlled in a ballistic sense, even when the COG lies outside the BOS, as long as the COM velocity lies within certain lower and upper bounds [1,2]. One can, therefore, infer from this work that LOB occurs if the COM velocity–position limits are exceeded in this chair rise task. Thus the balance theory proposed by Pai et al. is dependent upon COM position and velocity with respect to the BOS. On the other hand, Wu et al. proposed that a fall occurs when the speed of a certain point on the body exceeds a fixed absolute limit [3]. In that scheme COM position and BOS are not involved in the definition of a LOB. In a less quantitative approach, an attempt was made to distinguish between a LOB and slips, trips or falls in occupational accidents by defining LOB subjectively as 'any temporary situation whereby one loses or expresses a difficulty maintain-

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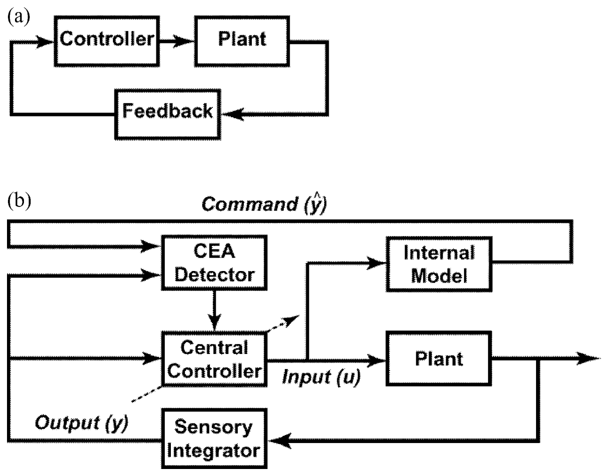

Fig. 1. Block diagram representations of the feedback control model of balance: in overview (a) and in more detail (b).

ing body equilibrium or stability' [4]. Clearly, differences of opinion exist on the physical definition of a LOB.

In the event of a fall, the only externally observable evidence that a human has perceived a LOB is an attempt to recover their balance, usually by a rapid adjustment of body configuration, such as the use of a compensatory step. Several studies have used this evidence to describe when the switch from a postural adjustment to a compensatory step becomes necessary as perturbation direction is varied and its magnitude is increased [5–8]. A compensatory stepping response turns out not to be a strategy of last resort, however, but is often initiated well before the COG is displaced outside the BOS [5,6]. This paper addresses the unknown mechanism(s) by which humans determine that a LOB has occurred.

Let us begin by positing that a 'LOB' is a loss of effective control of balance, as evidenced by the appearance of a control error anomaly (CEA) (see Section 4). We use the word 'control' here as defined in the OED: 'the fact of controlling, or checking and directing action; the function or power of directing and regulating'. Similarly, we use the word 'anomaly' here as it is defined by the same source: as an 'irregularity, deviation from the common order, exceptional condition or circumstance'. We therefore model the body as a mechanical system with an input signal, a controller, a plant, feedback of the output signal (Fig. 1a), and system states that are normally both observable and controllable. As long as the human is conscious, and we shall assume that to be the case in this analysis, the system controller monitors system states and stability via vestibular, visual and/or somatosensory afference.

When a human performs any balancing task, the system being controlled is inherently an unstable system, by definition of what it means to 'balance' a mass in a force field. In his authoritative text, Ogata defines control as 'the act of measuring the value of the controlled variable of the system and applying the manipulated variable (input) to the system to correct or limit deviation of the measured value from a desired value' [9]. Thus, whether in unsupported sitting, standing, or walking the body is unstable unless the central nervous control system exerts control over body configurations and its interactions with the environment. Its control system must also reject internal and/or external perturbations in order to prevent temporary instability about what control engineers call an 'operating point'. In the event of a CEA a change in control strategy is necessary to regain stability.

To identify what might trigger this change in strategy, we start by modeling the CNS control of balance using a model-reference adaptive control architecture (Fig. 1b). The proposed architecture has three main components: a forward internal model, the creation of the internal model using system identification techniques, and a failure-detection algorithm. The notion of an internal model being used by the CNS is not new. Wolpert et al. provided evidence for a forward internal model and proposed that the CNS internally simulates dynamic behavior of the motor system in planning, control, and learning [10]. Similarly, van der Kooij et al. showed that a control model with an internal model that includes knowledge of body dynamics, sensory dynamics and external environment can describe how humans compensate for environmental changes [11]. Although recent work has been based on an internal model and optimal estimation theory, there is no engineering description of how such a model may be created. Thus far, researchers have obtained the model pre-hoc from dynamic equations and anthropometry. As an example, Johansson et al. developed an optimal control model of posture and locomotion that used adaptive control in the case of unknown or uncertain parameters [12]. The parameters were updated as part of a linear regression problem with a least squares solution. Their model operates on the assumption that the initial model parameters are known. We shall examine the possibility, however, that the system might employ self-identification techniques to circumvent the requirement for a priori knowledge of initial model parameters.

In this work, a method is proposed whereby a dynamic description of the internal model of the task is created online, or bootstrapped from initial steady-state data, using system identification techniques. This has the advantage of on-line implementation and adaptation. In addition, the proposed method obviates the need for a priori knowledge or estimates of the model parameters. Based on the control error between the model and the plant output, on-demand adaptation (in the form of a large postural correction) is initiated in the event of a CEA. In the absence of a disturbance, we regard a CEA as a system failure resulting from a malfunction in one or more subsystems that tends to cause an undesired state [13].

Our next goal is to detect the CEA, the signal that triggers the attempt to correct the above system failure. The detection of CEA can be couched as a failure-detection problem involving both residual generation and decision-making. In physical terms, the controller must monitor the control error (or residual) between the model output (anticipated) and the actual output. The input is sent to both the model and actual plant (Fig. 1b). The residuals are analyzed by a sub-component of the controller we call the 'CEA detector' using a failure-detection algorithm (Fig. 1b). The CEA detector monitors the residuals and compares them to the maximum allowable limits. The failure-detection algorithm signals a CEA when the resulting residual crosses a pre-defined threshold (upper control limit) that we shall define as the 3Σ point (three standard deviations from the mean). This information is relayed to the central controller, where it is used in planning the control action.

Once the 3Σ threshold is reached, any compensatory response that is initiated is externally observable; this response is then confirmatory evidence that the controller was "aware" that its compensatory action was needed. Without this response, physical evidence of a CEA is not externally observable in terms of kinematic or kinetic quantities although, conceivably, newer brain imaging techniques might allow one to detect CNS neuronal responses.

In this study we assume that a CEA is an event that can be detected by an external observer monitoring the same physical parameters known to be observed by the CNS. Then a CEA can be defined to have occurred once a pre-defined control error signal e crosses a threshold level, e_{thresh}, set at three standard deviations (3Σ) above the mean of the baseline signal. We selected 3Σ because in this one-sided distribution this limit would constitute an unusual event, with a less than 1-in-700 probability of occurring if the error is assumed to be normally distributed.

The primary hypothesis (H1) that a CEA is detectable once the error signal reaches a 3Σ threshold was tested in healthy young volunteers asked to perform a balancing task so challenging that a CEA was inevitable. This only became obvious to them, however, after several trials. Physical confirmation of CEA was the onset of task failure within 2 s of the instant of CEA detection (T_{CEA}) (see Section 4). A secondary goal was to examine the reliability of using the 3Σ threshold to predict any impending compensatory response by testing the secondary hypothesis (H2): any compensatory reaction will invariably lag the instant of CEA by at least 100 ms. The 100 ms value was based upon results showing the fastest volitional human response time to be on that order [14,15].

2. Methods

2.1. Theoretical development

To test these hypotheses we considered the situation in which a person is attempting to balance themselves over the two rear legs of a chair (Fig. 2). The task was constrained by the condition that the person can only control his or her inclination by modulating the ground reaction forces (R_x, R_y, Fig. 2) between the dominant foot and the floor. This balancing task was modeled as an observer-based feedback control system consisting of an input signal (the foot force), a controller, a plant, an internal model, and feedback of the command signal (anticipated output) and of the actual output (angular position measure or its derivatives) (Fig. 1b). The plant represents the configuration maintained by the human body with the leg muscles as the actuators. Since the subject was completely supported by the chair, the subject and the chair may be modeled as a single inverted pendulum pivoting about the line between the rear feet of the chair, P, greatly simplifying calculations. The system thus modeled is governed by the following equation of motion:

$$I\ddot{\theta} = T + mgl\sin\theta \tag{1}$$

The system mass, moment of inertia, acceleration due to gravity, and distance from the pivot point to the COM are denoted by m, I, g, and l, respectively. The input, T, is the resultant ground reaction force acting on the dominant foot multiplied by its distance from the pivot point, and the angle, θ, is the angle of the COM with respect to the vertical (Fig. 2).

In the analysis, particular attention was paid to the control error, e, the difference between the output and command signals (Fig. 1b).

$$e(t) = y(t) - \hat{y}(t) \tag{2}$$

The output signal, y, represents the actual output, $\ddot{\theta}$, that the CNS has sensed through vestibular, proprioceptive, and/or visual signals. In the described task, however, this signal cannot be directly measured but was assumed to be externally observable as the acceleration of the chair. Physically, the command signal, $\hat{y}(t)$, is the resultant movement anticipated by the CNS due to the applied force. Using the system equation of motion, it was possible to obtain a parameterization of the internal model that would result in the command signal as a prediction of the high-frequency acceleration signal, $\ddot{\theta}$, based on a known input. Physical

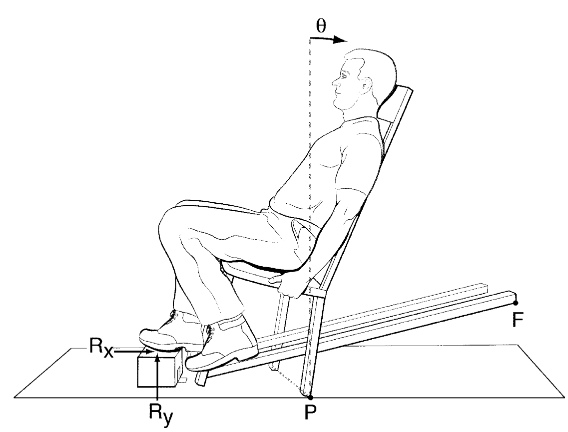

Fig. 2. Schematic of a subject starting his attempt to balance over the line 'P' by varying the unipedal reaction forces R_x and R_y. Unbeknown to the subject, the safety frame 'F' (along with padding on the floor, not shown) protects the subject from injury. It acts once the system has become unstable, is accelerating backwards, and has tipped backwards by an angle of 35° from the system balance position.

insight prompted us to separate the input signal into high and low-frequency components, T_{hf} and T_{lf}, respectively:

$$T = T_{hf} + T_{lf} \tag{3}$$

The resulting equation of motion for the system is:

$$\ddot{\theta} = \frac{1}{I} T_{hf} + \frac{1}{I} T_{lf} + \frac{mgl}{I} \sin\theta \tag{4}$$

To identify the controlled system and obtain parameter estimates for I, m, g, and l we started with a multiple, first-order polynomial model:

$$\hat{y}(t) = c_0 + c_1 u_1(t) + c_2 u_2(t) + c_3 u_3(t) \tag{5}$$

where $u_1 = T_{hf}$, $u_2 = T_{lf}$, $u_3 = \sin(\theta)$.

This equation represents a black-box model of the plant. The output, $\hat{y}(t)$, is the model prediction for the acceleration output, $\ddot{\theta}$. In accordance with the objective of identifying the controlled plant, u_3 was removed as a regressor in (5) since it was not a control input. Statistical analysis of the two remaining regressors (T_{hf} and T_{lf}) showed that T_{hf} had the greatest significance ($P < 0.001$). Therefore, in the interest of simplicity, we used a simple first-order polynomial with T_{hf} as the single input, $u(t)$:

$$\hat{y}(t) \;=\; c_0 + c_1 u(t) \tag{6}$$

The parameters c_0 and c_1 were obtained using least-squares optimization applied to a steady-state interval of 2 s at the start of the balancing task. The model was then used to simulate the anticipated output given the measured input for the duration of the task.

Merging (2) and (6) yields (7), after re-defining e as the residual generated when the actual chair acceleration is compared with the predicted output of a simple first-order polynomial model (Fig. 3a, b).

$$e(t) \;=\; y(t) - \hat{y}(t) \;=\; \ddot{\theta} - (c_0 + c_1 T_{hf}) \tag{7}$$

The 3Σ threshold algorithm detects a CEA when e crosses the threshold set at three standard deviations (3Σ) above the mean of the baseline performance data, as shown in Fig. 4. Also included in Fig. 4 are the following details. First, the model parameters were identified at the beginning of the trial using the data in the fixed, 2-s window, a. The baseline performance data is obtained from b, a 2-s forward-moving trailing window, which lagged the current time instant, t, by 100 ms. The mean, μ_b, and standard deviation, Σ_b, obtained from this window were then used to calculate the threshold e_{thresh} at time t, 100 ms later (9). Calculation of the moving threshold commenced at 'Start', initially using the data in a as baseline data, with a 100 ms delay (δ) to allow for neural

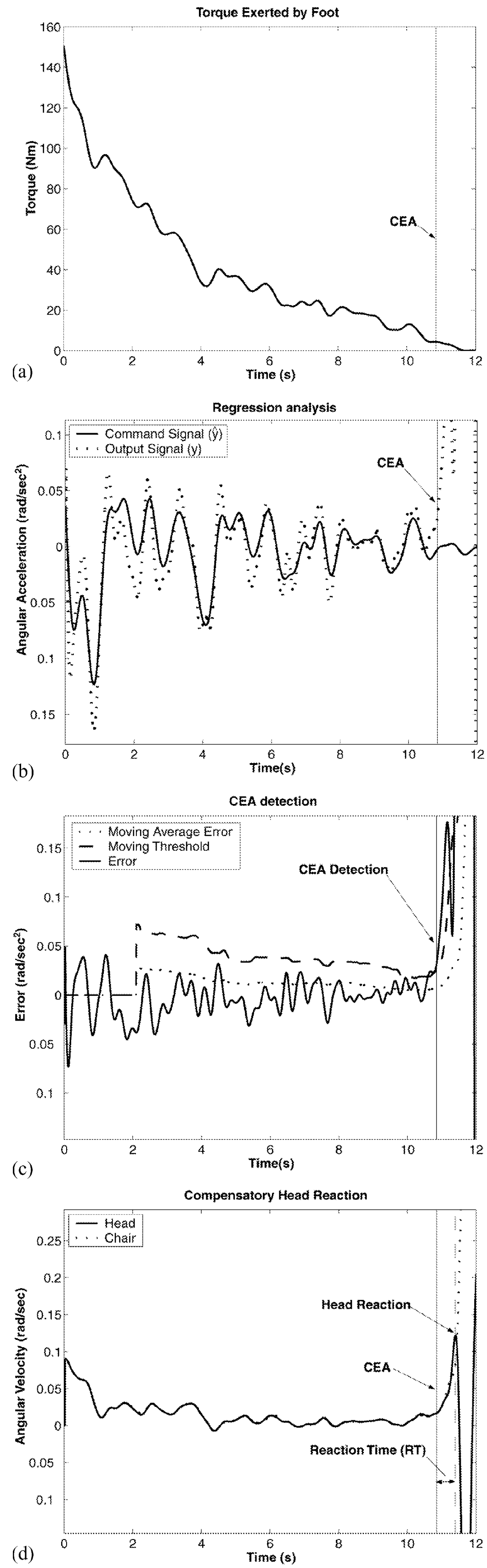

Fig. 3. Sample time history of each parameter from one subject along with an illustration of the implementation of the data analysis methods: (a) time history of the torque applied by foot; CEA onset is marked by the solid vertical line; (b) corresponding calculated command and output signals; (c) calculated control error (e) signal; (d) reaction onset.

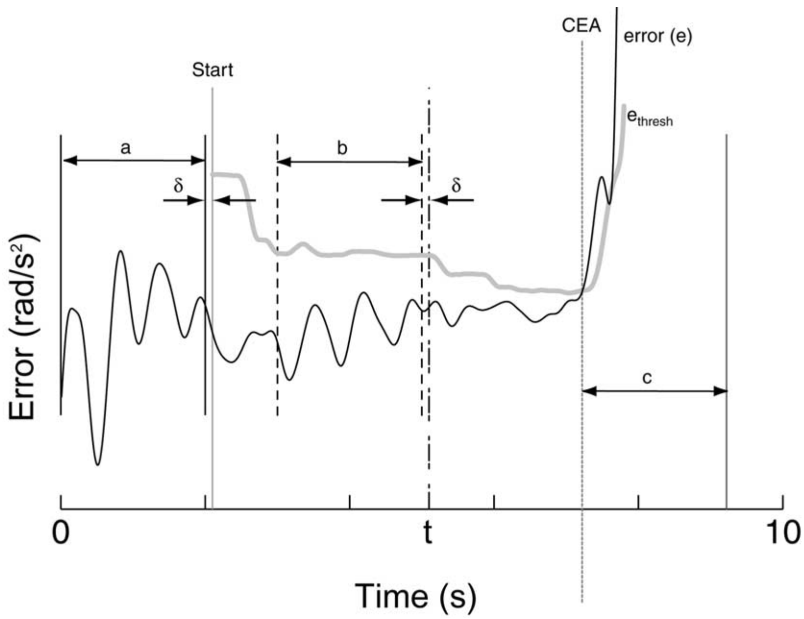

Fig. 4. Sample time history of the error (black) and e_{thresh} (gray) signals from one subject along with timing marks illustrating the salient variables given in the text. The CEA is detected once e crosses e_{thresh}. Points 'F' on the chair must strike the ground within window 'c', a 2-s limit following CEA. Any voluntary or involuntary reaction must occur no earlier than 100 ms after CEA.

processing [11]. The moving 2-s window, b, continues to move through the trial, calculating the threshold 100 ms later. A CEA is detected when:

$$e > e_{\text{thresh}}, \quad (8)$$

where

$$e_{\text{thresh}} = \mu_b + 3\Sigma_b \quad (9)$$

and μ_b is the mean, and Σ_b is the standard deviation of the window:

$$b = e_{(t-2.1\ \text{s}):(t-0.1\ \text{s})}$$

In addition to the 3Σ threshold error criterion, the head (and chair) angular acceleration and velocity at time t must exceed published vestibular sensory thresholds, 0.00087 rad/s^2 and 0.017 rad/s, respectively [16,17].

2.2. Experimental setup and procedure

Twenty healthy, young adult volunteers (ten males and ten females) aged 18–25 years were tested. Males and females had an average height of 176.6 ± 4.8 and 167.55 ± 5.0 cm, respectively. All subjects gave written informed consent as approved by the institutional Internal Review Board.

Subjects were tested in a sagittally-symmetric posture while sitting in a sturdy, four-legged experimental chair with a rigid head rest (Fig. 2). The legs and arms were maintained in a neutral posture, neither ab- nor adducted. Shoes were not removed. Subjects were asked to grip the seat with one hand on either side. A 200 N capacity two-axis force-transducer was placed under the metatarsal joints of the dominant foot. A lead brick was placed as a spacer between the foot force-transducer and the floor so that the initial posture of the ankle joint was neutral. The contralateral foot rested on the chair frame.

The subject was asked to push down with the metatarsal joints of their dominant foot in order to push themselves slowly backwards until they (and the chair) were perfectly balanced "for as long as possible" over its rear legs, P, with no foot–ground contact. The dominant foot force was the sole input to the one degree-of-freedom mechanical system comprised of the subject and chair. To ensure this, the subject was asked to constrain the head, neck, and torso as a rigid body by using the chair for full support, and was directed to maintain contact between their head and the support while they were balancing. To ensure the subject's safety, the horizontal rungs of the chair were extended backwards by 1 m in order to prevent the chair from rotating backwards by more than 35° with respect to the vertical, thereby preventing a backward fall (Fig. 2). Each subject performed ten trials with their eyes open. No practice trials were allowed.

2.3. Data acquisition

Body segment kinematics, and foot (vertical and horizontal component) reaction forces were recorded. Head orientation and location in three-dimensional space were measured at 100 Hz using infrared head-mounted light-emitting diodes (LED) markers and an Optotrak® 3020 motion analysis system to the nearest tenth of a mm. Three non-collinear LEDs were affixed to a headband oriented in the Frankfort plane. One LED was attached to the chair's rear leg, and one to the headrest, allowing the inclination of both head and chair to be measured throughout the trial. The foot reaction forces were recorded after amplification to volt levels at 100 Hz using a 12 bit analog-to-digital converter and microprocessor.

The kinematic data were low-pass filtered with a cut-off frequency of 3 Hz using fourth-order Butterworth filter (Matlab®) and differentiated using a five-point differentiation algorithm to obtain velocity and acceleration data. The force data were also filtered with a fourth-order, low-pass Butterworth filter (Matlab®) and a cutoff frequency of 3 Hz. The high and low-frequency components of the filtered force signal were separated using a cutoff frequency of 0.3 Hz and all filtering routines were employed forward and backward to minimize phase shift artifact.

Bilateral sternocleidomastoid myoelectric data were recorded at 2 kHz from bipolar surface electrodes (2 cm spacing) and root-mean-square values calculated. However, subsequent analyses showed that these signals were too variable to be useful as markers of the first response to a CEA (see Section 4). This data was, therefore, omitted from the analysis and an alternative method was employed to determine the onset of a first response.

2.4. Data analysis

The appearance of the first observable response, often a righting reflex and consisting of a large flexion acceleration of the head, neck and/or torso, was taken as first evidence that the CNS recognized system performance as inadequate. Detection of the onset of this movement was achieved by monitoring the difference between the angular velocity of the head and the chair. Once the difference increased to a level greater than ten standard deviations above the mean of past data, head movement was confirmed. Commencement of the reaction was then traced back to the onset of the response by visual inspection. Reaction time (RT) was defined to be the duration between the instant of CEA detection (T_{CEA}) and onset of the response (Fig. 3d).

To test the primary hypothesis, each trial was labeled as ‘successful’ if T_{CEA} preceded the instant that the chair safety stops, F, struck the ground by less than 2 s, the maximum time that the chair could physically take to fall backward. To test the secondary hypothesis, each trial was labeled as ‘successful’ if the compensatory reaction lagged the CEA by at least 100 ms, i.e. RT was greater then 100 ms.

Tests of the primary and secondary hypotheses were conducted using the 3Σ algorithm. However, we also tested the hypotheses using an alternative algorithm that estimated the instant of CEA using fixed kinematic thresholds in the manner of Wu [3]. This method searched the duration of the trial for excessively large values of chair angular acceleration and/or angular velocity greater than 0.1 rad/s^2 and 0.03 rad/s, respectively. These values were determined empirically. The performance of three algorithms using the three possible combinations of these fixed kinematic thresholds i.e. 0.1 rad/s^2 (designated ‘Acc’), 0.03 rad/s (‘Vel’), 0.1 rad/s^2 and 0.03 rad/s (‘Acc/Vel’), was compared with the detection and predictive abilities of the 3Σ algorithm.

A sensitivity analysis was conducted on the 3Σ algorithm parameters to determine their respective effect on the successful detection of CEA. Values for the vestibular sensory threshold, size of the parametric identification (ID) window, size of the moving window, and the high-pass frequency cutoff used to separate the force signal were all varied in increments of 25% of their original value (Table 2).

Gender differences were examined using the independent two-sided *t*-test, and trial effect was evaluated with a single factor analysis of variance, with $P < 0.05$ being considered statistically significant.

3. Results

The results indicate that the 3Σ algorithm reliably detected a CEA 2 s before the chair safety stops, F, contacted the ground. The test of H1 was conducted on the set, N_1, of all 197 trials (98 male and 99 female subject trials). The algorithm detected CEA with a 94.4% success rate (Table 1). The average time between T_{CEA} and the instant the chair safety stops hit the ground, T_F, was 1.01 s. One female trial was lost due to software difficulties and two male trials were not included due to excessive head movement. All CEA

Table 1
Performance statistics of the 3Σ algorithm

	Males	Females	All subjects
Hypothesis H1			
Total trials, N_1	98	99	197
Successful CEA detection, L, L/N_1%	94, 95.9%	92, 92.9%	186, 94.4%
Average T_F (SD) (s)	0.99 (0.168)	1.03 (0.186)	1.01 (0.177)
Hypothesis H2			
Trials with reactions, N_2	94	82	176
RT>100 ms, R, R/N_2%	86, 91.5%	77, 93.9%	163, 92.6%
Average RT (SD) (ms)	443.4 (192.2)	514.6 (205.4)	479.0 (199.1)

The number of trials supporting the hypothesis H1 and H2 are denoted by L and R, respectively. The corresponding success rates (in %) are also given, along with relevant temporal information.

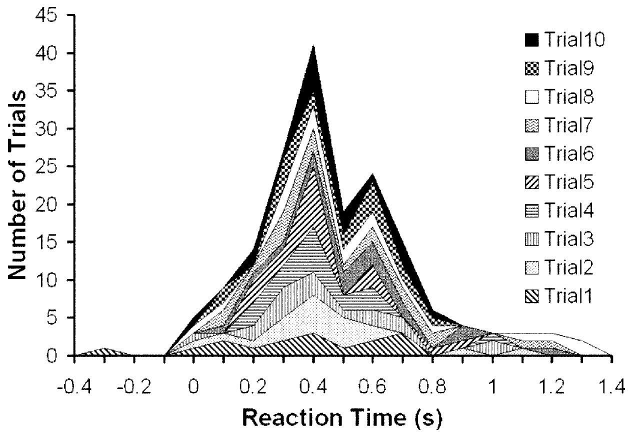

Fig. 5. Frequency distribution of RT by trial number across all subjects.

detection failures were false positives, i.e. CEA was detected more then 2 s before the chair stops hit the ground. Ten out of these 11 failures exhibited both significantly lower absolute error and angular acceleration at T_{CEA} than did the successful trials ($P < 0.0001$).

In testing H2 only the set, N_2, of trials exhibiting a compensatory reaction and a successfully-detected CEA could be analyzed, so this number was a subset of N_1 (Table 1). The algorithm successfully predicted a compensatory response in N_2 that lagged T_{CEA} in 163 (92.6%) of the 176 trials; 12 female trials could not to be used due to the lack of a compensatory reaction (see Section 4). For both males and females, a significant proportion of RTs were greater than the hypothesized 100 ms minimum ($P < 0.001$) (Fig. 5). The following results were calculated using the data from the 163 trials in which the compensatory reaction was predicted successfully. There was no significant statistical difference between the RTs exhibited in males and females ($P < 0.30$), nor a significant trial effect on RT ($P < 0.35$). The average RT was 479.0 ms; longer RTs were associated with low velocities and accelerations at T_{CEA}, and vice versa. A linear regression analysis using least squares fit a logarithmic trend line ($R^2 = 0.82$) through a series of points representing the average RT of all trials exhibiting a velocity within a 0.01 rad/s interval. Similarly, a logarithmic trend line ($R^2 = 0.48$) described the relationship between RT and acceleration at T_{CEA} (Fig. 6).

There was no significant trial effect on the success of either H1 or H2. An analysis of only the first five trials across all subjects provided success rates of 91.92 and 93.18% for H1 and H2, respectively. The average RT was 426.0 ms.

The optimal threshold level was found to be 3Σ; lower levels resulted in more false positives, while higher levels

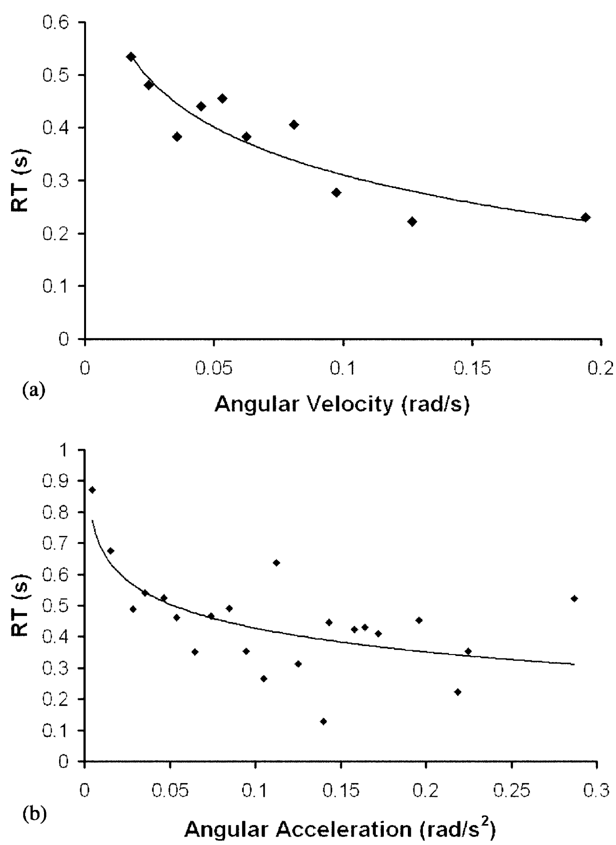

Fig. 6. Plots of (a) RT vs. velocity at T_{CEA} with logarithmic trend line $y = -0.1311\ln(x) + 0.0087$; and (b) RT vs. acceleration at T_{CEA} with logarithmic trend line $y = -0.1107\ln(x) + 0.173$. The data shown are for the 163 trials exhibiting compensatory reactions (Table 1).

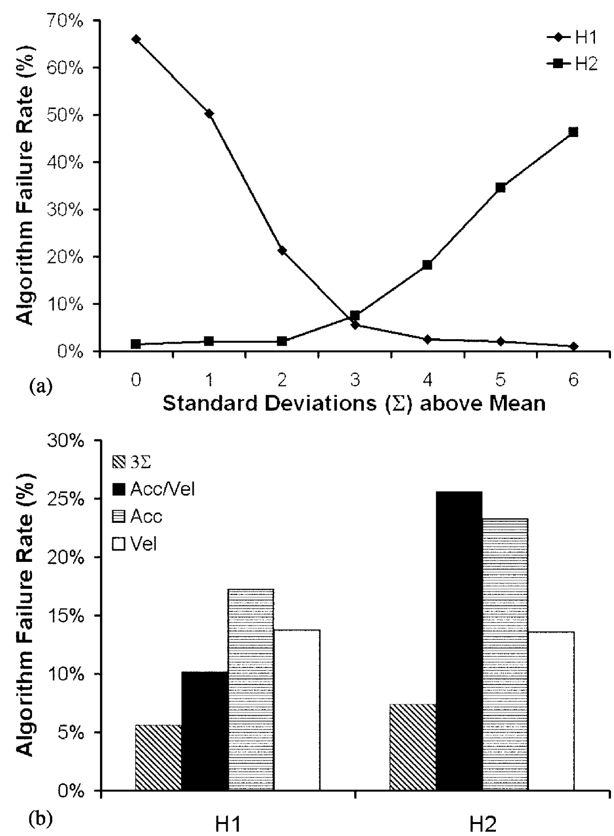

Fig. 7. Results of algorithm sensitivity to changes in threshold: (a) effect of threshold magnitude on algorithm failure rates; and (b) a comparison of algorithm performance using the 3Σ criterion and three examples of a fixed kinematic threshold.

Table 2
Sensitivity of successful CEA detection and reaction prediction (in %) to systematic changes in algorithm parameter values

Algorithm parameters		Percent change in parameters							
		−75%	−50%	−25%	Original	+25%	+50%	+75%	+100%
Sensory thresholds (rad/s)		2.18e−4	4.35e−4	6.53e−4	8.7e−4	10.9e−4	13.04e−4	15.23e−4	17.4e−4
(rad/s^2)		0.00425	0.0085	0.01275	0.017	0.02125	0.0255	0.02975	0.034
	H1 (%)	64	76	85	94	99	99	99	100
	H2 (%)	96	95	95	93	86	86	82	79
ID window (s)		0.5	1	1.5	2	2.5	3	3.5	4
	H1 (%)	91	93	93	94	93	90	89	89
	H2 (%)	85	91	91	93	90	89	89	89
Moving window (s)		0.5	1	1.5	2	2.5	3	3.5	4
	H1 (%)	67	84	89	94	96	95	96	94
	H2 (%)	94	91	92	93	92	92	90	89
Cut-off frequency (Hz)		0.075	0.15	0.225	0.3	0.375	0.45	0.525	0.6
	H1 (%)	94	93	90	94	94	94	96	97
	H2 (%)	85	86	88	93	93	94	92	91

resulted in delayed CEA detection times (Fig. 7a). The algorithm performance was relatively insensitive to 25% changes in the vestibular sensory thresholds, the size of the moving or ID windows, or the cutoff frequency (Table 2). The goodness of fit (R^2) of the internal model regressed from the 2 s identification window at the start of each trial also varied with the high-pass cutoff frequency, forming an inverted U-shaped distribution with a maximum R^2 value of 0.79 (averaged across all trials and all subjects) at 0.3 Hz (Fig. 8).

All three combinations of the algorithm employing fixed kinematic thresholds provided reduced rates of success in detecting CEA and in predicting a compensatory response (Fig. 7b). In those trials in which CEA was detected successfully, both the Acc and Acc/Vel thresholds provided less average recovery time before the chair stops hit the ground than did the 3Σ algorithm (0.82, 0.87, and 1.01 s, respectively).

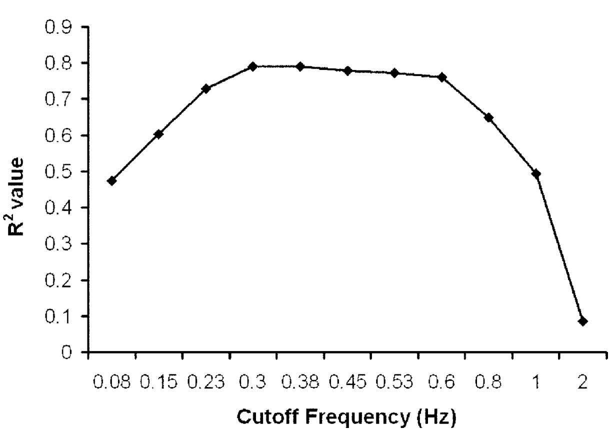

Fig. 8. Plot of R^2 values for the internal model regressed from the 2 s identification window (averaged across all trials for all subjects) vs. high-pass cutoff frequency.

4. Discussion

The findings of this study support the first hypothesis, H1, that a CEA can be detected by tracking externally-observable physical input and output parameters while healthy subjects perform a challenging balancing task. The scheme involves comparing the current system residual with a 2-s aggregation of past states, accumulated when the system was known to be controlled.

The presence and timing of a compensatory reaction (H2) provides evidence for a CEA as a valid indicator of a LOB. The fact that CEA is detected using signals normally observable to the CNS suggests that the CNS may have indeed detected a CEA and responded to it. Using position–velocity stability limits, Pai et al. were able to predict a compensatory stepping response in 65% of experimental trials [2]. The 3Σ algorithm, using the high frequency components of an acceleration-based measure of how well the movement is controlled, provided a higher prediction of a compensatory reaction (92.6%). The trials in which the algorithm failed to successfully predict a compensatory response may have been the result of a conservative strategy on the part of the subject, or increased values of velocity and acceleration.

When the absolute values of the error and acceleration were uncharacteristically low, the algorithm failed to correctly detect a CEA despite the 3Σ threshold being exceeded. This result implies that perhaps, in addition to a moving relative threshold on the error, a fixed minimum error threshold could be added to the algorithm if needed.

It is noteworthy that the reliability of the 3Σ algorithm in detecting a CEA, and predicting a compensatory reaction, was greater than when using a competing method based on fixed angular acceleration and/or velocity thresholds. Disadvantages of using fixed kinematic thresholds are their dependence on the task as well as the need for their a priori empirical determination. Wu et al. used fixed thresholds on horizontal and vertical velocity to detect falls an average of 0.42 s before the end of the fall [3]. In the present paper, the 3Σ algorithm not only provided greater response time before the end of the fall (1.01 s), but it could also predict a recovery reaction.

The present model uses system identification techniques to create an internal model online. This strategy contrasts with earlier efforts. Although the idea of an internal model is familiar, its creation without any assumption about initial parameters is, we believe, novel. Despite the fact that in this chair balancing task, subjects had no knowledge of the mass or mass distribution of the chair and, prior to the first trial, were not permitted to experiment with it, the online system identification worked satisfactorily.

4.1. Effect of algorithm parameters

An identification window of 2 s provided the regression analysis with 200 observations and proved optimal for reliable parametric identification in this task (‘ID Window’ in Table 2). However, three trials only allowed 1 s for system identification, due to their brief duration (3 s). The effect of the duration of the identification interval on this and other tasks, and the dynamics of parameter identification with respect to changing tasks, environments, and learning, are worthy of further investigation. Body segment movements may be modeled internally and the accuracy of that model would affect decisions concerning the state of the system, and the timing and choice of a postural correction.

Another important aspect of the system identification is the cutoff frequency used to separate the filtered input signal in preparation for the regression analysis. In order to reliably predict the output signal, the regression analysis was only applied to the frequency range of the input signal in which a sinusoidal input would result in an output signal of steady amplitude. The cutoff frequency approximates the −3 dB point of the linearized system’s frequency response, when the amplitude of the output response to the input has been reduced by 3 dB. Applying a lower or higher cutoff frequency will decrease the goodness of fit of the internal model, decreasing the algorithm’s success in both detecting CEA and predicting a compensatory reaction (Fig. 8). This implies that the accuracy of the internal model is highly important for the successful initiation of this reaction.

The size of the moving window used by the algorithm is a function of the frequency content of the error signal. The algorithm operates on the assumption that a value outside the 3Σ limits has a 0.13% chance of occurrence and thus is probably a CEA. This rule only applies, however, if the data is normally distributed. The moving window must, therefore, be large enough to provide data with a normal amplitude distribution. In addition to optimal window size, the model itself should be sufficient to provide normally-distributed residuals.

The 2-s limit, applied following detection of the CEA in order to furnish evidence of task failure, was based on knowing that the chair and subject together took approximately 1 s to fall from the balance point to the ground. An additional second was added because the occurrence of a compensatory reaction would slow this descent. We also assumed that in order to maximize the likelihood of a recovery, the CNS would detect a CEA before the onset of the fall if possible. A longer limit would have compromised the selectivity of the algorithm.

For this particular task, an upper threshold on the error was used to detect CEA, reflecting the fact that the control input and threat of injury were unidirectional. This was because only positive error, evidence of excessive posterior acceleration, was cause for concern. In tasks in which the control input and/or the threat of injury is bi-directional, both upper and lower thresholds on the error signal would be implemented.

4.2. On the compensatory response

Our CEA theory does not require that the first observable response is necessarily a reflexive or righting response. It simply has to be the first observable change in control strategy, whether appropriate or not. In the case of a novel balancing task, that response may well be inappropriate and even detrimental; in the case of a well-learned and familiar task, it would usually be both appropriate and efficacious.

The rationale for using the head flexion response as the indicator of a change in control strategy is that it was the most common, and probably the most efficacious, response to the CEA in this particular balancing task. When it occurs, this obvious change in control strategy suggests that a CEA had been detected by the CNS. Although other reactions were exhibited by subjects, including vocalization, a large change in foot force, and/or raising the hands or arms, the head reaction was the most consistently-exhibited reaction. A large change in foot force may be ambiguous because it could simply be a variation of the original control strategy of modulating the ground reaction force, and the vocalization has no effect on system control. In fact most subjects only used the head flexion response and this either preceded or occurred simultaneously with any lifting of the hands or arms.

Subjects were instructed to maintain contact between their head and the head support on the chair while they were controlling the chair, thereby inhibiting the vestibulospinal reflex and ensuring that any recovery reaction was voluntary. It also allowed us to determine, from the change in head velocity relative to the chair, when a change in control strategy occurred. An additional assurance that the movement was indeed voluntary was the requirement that the RT had to be greater than 100 ms, or on the order of the fastest voluntary head movement RTs (107 ms) recorded in seated subjects [14]. Reflexive head movements due to whole-body linear acceleration are known to be shorter than this, with latencies in the range of 73–81 ms [18].

Even though root-mean-square sternocleidomastoid myoelectric (EMG) data were measured for all the subjects, a pilot analysis demonstrated that they proved unreliable as an indicator for CEA. This was due to muscle pre-activation, and therefore, increased variability, caused by subjects tending to coactivate the neck musculature as they approached the balance point. So the EMG data were not used in any further analyses.

4.3. Limitations

This study has several limitations. First, the only task that was studied relied on continuous feedback control. It remains to be determined whether the 3Σ algorithm will work for tasks, such as gait, that involve intermittent feedback and control of surface reaction forces. Second, we have not attempted to identify any of the neural structures that might implement the proposed control scheme. Wolpert et al. have provided results that point to the location of internal models as being in the superior parietal lobe [19]. As for CEA detection, the cerebellum may well be involved since it is known to evaluate the error between intention and action [20]. Thus CEA detection may likely occur in the higher centers of the CNS, along with the inherent transmission delays to and from an involved extremity thereby engendered. Third, the algorithm requires an initial steady-state interval to identify the internal model. In real life, this interval is not available in some tasks and the CNS must then base the internal model on recall of prior experience with similar activities. Fourth, the onset of the reaction was determined by visual inspection, and is therefore, open to subjective bias. However, the potential error in estimating RT could not have been greater than 5% due to the rapidity of the reaction.

The final limitation is that subject habituation may have affected the compensatory reaction. Once subjects lost control, they were instructed to attempt to save themselves in any way possible, with the exception of grabbing an external structure. But once the system became unstable, it was extremely difficult to stabilize, due to its considerable inertia as well as the small magnitude of the available restoring torque (developed by lifting the weight of the foot and dominant limb from the force transducer). In addition, due to the fact that we had to provide safety stops to reduce injury risk, some subjects eventually realized after several trials that the compensatory reaction was not mandatory. As a result, a few subjects eventually appeared to choose not to react. However, 11 of the 12 trials lacking compensatory reactions occurred in just two such subjects. Other evidence that subject adaptation had taken place during the ten trials also comes from RTs being lengthened, perhaps by an increasing lack of urgency in response. So, any lack of urgency with which a subject triggered a reaction skewed the RT distribution to the right in Fig. 5. Future work might focus on tasks in which the compensatory reaction and the urgency of its use are inherently assured. Lastly, the longer RTs that we observed may also be a result of lower velocities and accelerations. For example, Nashner et al. also found an inverse relationship between response times and postural sway rate [16]. In the event of the smallest velocity values, response times were on the order of 1.4 s, similar to the maximum RTs observed in this task.

4.4. Why control error anomaly rather than loss of stability

We have already noted that any human balancing task involves the control of an inherently unstable system, by definition. Therefore, a discussion of the concepts of control or balance, must address the question of stability and loss of stability. In this study we define a CEA as occurring when the control error signal crosses a threshold (or bound) set at 3Σ, i.e. the system has failed to respond to the given input with an output within a certain limit. Thus a CEA in a balancing task implies a loss of stability (and vice versa) in the sense that the system has failed to respond to a bounded input with a bounded output. Over 300 years ago, Francis Bacon once wrote, ‘Whereas the meaning ought to govern the term, the term governeth the meaning’ [21]. We, therefore, use ‘control error anomaly’ here in preference to ‘loss of stability’ for several reasons. First, it describes the underlying mechanism and underscores the recognition of an unusual event that occurs after skill has been achieved in the performance of a motor task. Second, because there are many different notions of stability (e.g. asymptotic, conditional), in static, dynamic, passive or nonlinear systems, ambiguity results from using the term ‘loss of stability’ since that term does not technically imply that a control input is present. To those in the fields of mechanical dynamics and control theory, notions of stability have rigorous definitions and are often restricted to simplified system types, such as linear systems. The question of the stability of human balance, however, cannot usually be simplified to consideration of the stability of a linear system. Therefore, following Bacon’s advice, we believe that a CEA more accurately describes the physical behavior underlying a LOB while circumventing possible misinterpretation of the term ‘loss of stability’.

4.5. Methodological advantages

The simplicity of the model used to predict the anticipated output is attractive. It suggests that, in this challenging balancing task at least, knowledge of COM position is not critical to identifying and predicting the system dynamics. Using only the frequency components of the input signal corresponding to the bandwidth of the output signal’s frequency response, and a basic linear additive model, it was possible to predict system performance fairly reliably.

Therefore, one novel aspect of the 3Σ threshold hypothesis is that it does not require the CNS to use position feedback in the control of balance; any input that can reliably predict the expected output will suffice. The output is also not restricted to an acceleration signal; the only requirement is that the signal be dependent upon the input, and that this relationship can be quantified as an internal model. Furthermore, this method can be expanded to incorporate multiple inputs, outputs, and error signals in the case of multi-segment movement. Finally, the CNS does not need to identify where the COM is in order to detect a CEA. This is in contrast to many postural control theories that assume the body's COG must be maintained within its BOS [22–24]. The method does not require the existence of absolute position cues, and the boundaries of the BOS do not need to be calculated. It can, therefore, be used to analyze quasi-static and dynamic tasks alike, provided that a sufficient internal model can be generated. The lack of a dependence on a fixed reference position means the 3Σ threshold hypothesis may have application in the design of fall detectors applied to the elderly as well as to the automatic control of ambulatory robots.

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