Published in final edited form as:

Exp Brain Res. 2009 October ; 199(1): 1–16. doi:10.1007/s00221-009-1956-5.

Neural basis of postural instability identified by VTC and EEG

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Abstract

In this study, we investigated the neural basis of virtual time to contact (VTC) and the hypothesis that VTC provides predictive information for future postural instability. A novel approach to differentiate stable pre-falling and transition-to-instability stages within a single postural trial while a subject was performing a challenging single leg stance with eyes closed was developed. Specifically, we utilized wavelet transform and stage segmentation algorithms using VTC time series data set as an input. The VTC time series was time-locked with multichannel ($n = 64$) EEG signals to examine its underlying neural substrates. To identify the focal sources of neural substrates of VTC, a two-step approach was designed combining the independent component analysis (ICA) and low-resolution tomography (LORETA) of multichannel EEG. There were two major findings: (1) a significant increase of VTC minimal values (along with enhanced variability of VTC) was observed during the transition-to-instability stage with progression to ultimate loss of balance and falling; and (2) this VTC dynamics was associated with pronounced modulation of EEG predominantly within theta, alpha and gamma frequency bands. The sources of this EEG modulation were identified at the cingulate cortex (ACC) and the junction of precuneus and parietal lobe, as well as at the occipital cortex. The findings support the hypothesis that the systematic increase of minimal values of VTC concomitant with modulation of EEG signals at the frontal-central and parietal–occipital areas serve collectively to predict the future instability in posture.

Keywords

VTC; Balance; Falling; EEG; Wavelet; ICA; LORETA

Introduction

To sustain an upright posture, the muscles of the postural control system must support the body against gravity, stabilize the supporting elements of the body when other elements are moved and ensure that the body is balanced through the vertical projection of the center of gravity lying within the base of the support (Rothwell 1994). However, in spite of the longstanding general acceptance of this principle, it is still unclear what kind of information the postural control system may use to sustain upright posture and predict future instability. Traditionally, the amount of motion of the center of pressure (COP) away from the equilibrium point was assumed to be a reflection of the degree of instability and served as a controllable variable in the regulation of the upright posture (Goldie et al. 1989; Murray et al. 1975).

A contrasting view holds that it is not the departure from the stability point within the equilibrium region per se, but rather the spatial and temporal dynamics of the COP with respect

to its stability boundaries that characterizes the stable versus non-stable standing postures, both in young controls (Martin 1990; Riccio 1993; Slobounov et al. 1997; Haibach et al. 2007), elderly (Slobounov et al. 1998; Van Wegen et al. 2001, 2002) and patients suffering from orthopedic and neurological disabilities (Hertel et al. 2006; Hertel and Olmsted-Kramer 2007; Slobounov et al. 2008). This more recent experimental work has been driven by the proposition that the virtual time to contact (VTC¹) with the stability boundary may be a low-dimensional information control variable in the regulation of upright posture (Carello et al. 1985). Accordingly, time-to-contact measures may yield information about dynamic stability in balance (Patton et al. 1999; Van Wegen et al. 2001; 2002; Haibach et al. 2007) and serve as a “detector/predictor” of future instability.

Slobounov et al. (1997) developed an approach and method to determine the virtual time to contact (VTC) to the stability boundary in a two-dimensional space, and applied this method to the estimate of postural stability in human standing posture. Figure 1 shows a schematic representation for the calculation of VTC (see also the algorithm for calculation of VTC in Appendix). In a series of studies in our laboratory, VTC has been shown to be a more sensitive measure of the decline in postural stability with advancing age than traditional center of pressure based measures (Slobounov et al. 1998; Haibach et al. 2007). Van Wegen et al. using a variation of this virtual time-to-contact measure, have shown similar age-related properties of time to contact in the control of postural stability (Van Wegen et al. 2001, 2002). Hertel et al. (2006) have shown the robustness of the virtual time-to-contact measure in human single leg postural standing. More recently, Hertel and Olmsted-Kramer (2007) revealed changes of time-to-boundary measures in subjects suffering from chronic ankle instability and suggested that the time-to-boundary measures may detect postural control deficits that are not detected by traditional measures (i.e., center of pressure range (COP) and velocity, etc.).

VTC has also been used to assess the deficits of postural control in subjects suffering from mild traumatic brain injuries. Indeed, we observed significant alterations in VTC in terms of absolute values, range of VTC at the deflection points and mode at the day 30 post-injury in subjects suffering from mild traumatic brain injuries (Slobounov et al. 2008). Interestingly, these subjects were clinically asymptomatic on the testing day, and no significant differences for any of the standard COP-based measures of postural control (i.e., 90% ellipse COP area, COP velocity, and stability index) were observed. The deficits in VTC control may indicate the residual postural abnormality in subjects suffering from mild traumatic brain injury and provide further evidence that VTC is an information property used by the CNS to regulate dynamic postural movement. This study provided further evidence that VTC is a sensitive measure of instability that may act as a control variable in the regulation of upright standing posture (Slobounov et al. 1998; Van Wegen et al. 2001, 2002; Haibach et al. 2007).

There are several reports that provide at least indirect evidence for the existence of neural substrates of time-to-contact measures. For example, the neural representation of time to contact has been identified via activation of looming sensitive neurons (e.g., nucleus rotundus) during pigeons' reaction to image expansion of objects approaching on a direct collision course (Ring and Simmons 1999; Sun and Frost 1998). Similar neuron response types were identified in the locust's visual cortex (Judge and Rind 1997) suggesting again that time to contact may be represented in the CNS. More recent computational models posit the existence of cortical “boundary vector cells”, the activity patterns of which encode the animal's distance from the salient geometric borders. The existence of the cells that fire when an animal get close to the borders of the proximal environment has been recently documented (Solstad et al. 2008). These border cells encode the periphery of the environment and are tuned to barriers more generally,

¹As used in human postural control research, VTC has also been referred to as “time to boundary” (e.g., Van Wegen et al. 2002; Hertel et al. 2006), “time-to-contact, TtC” (Haddad et al. 2006; Hasson et al. 2008).

irrespective of their continuity with the other borders. It was shown that these border cells also respond to boundaries other than walls, including the open surface with a drop on all four sides.

In humans, a recent fMRI study has also demonstrated that the parieto-frontal system is specifically activated during judgment of time to contact (Field and Wann 2005). Similarly, Slobounov et al. (2005) observed a burst of EEG gamma activity at the frontal-central-parietal areas preceding the initiation of compensatory postural movement when balance was in danger. These brain imaging studies support the notion that there are specialized neural detectors for goal-oriented behavior in general (Mataric and Pomplum 1998) and for detecting postural instability, in particular (Slobounov et al. 2000).

In this study, we investigate the neural basis for signaling the future instability of standing posture as reflected in the dynamics of VTC in conjunction with EEG measures. The experimental situation was designed to directly provoke the subjects to lose balance so that we can examine both behavioral (postural data with specific focus on VTC) and EEG measures associated with pre-falling stable and transition-to-instability stages within a single postural trial. We investigated the hypothesis that the postural control system detects and predicts future instability via VTC information dynamics, thus eliciting the activation of certain brain structures identified by EEG.

Methods

Subjects

A total of 12 healthy young adults without any acute orthopedic injuries to the lower extremities participated in this study (seven male, five female aged 22–24 years old). All subjects were right-handed (laterality index was 0.8–1.0) as measured by the Edinburgh Inventory (Oldfield 1971). The protocol was approved by the Pennsylvania State University Institutional Review Board, and the subjects gave their written consent for the study prior to the experimental session.

Tasks and procedures

The subjects were required to stand on one leg (both right and left) with eyes closed as still and as long as possible. There were three trials for each leg stance. The loss of balance ultimately observed at the end of the trial was also identified when subjects took a step and/or initiated unsuccessful compensatory strategies to regain balance (i.e., hops, jumps, elevating heel, etc.). Subjects wore a harness to protect them from hitting the ground in case of actual occurrences of falling. Otherwise, the harness was adjusted in such a way that it did not provide any weight suspension and/or other sensory information to the subject. The order of left/right leg stance condition was randomized between subjects. Thus, we designed this experiment with the specific intention of provoking the subjects' loss of postural stability and examining both behavioral (postural measures) and its neural (EEG measures) underpinnings during stable and transitional stages of postural control.

Postural data acquisition

An Advanced Mechanical Technology, Inc. (AMTI) force platform was used to collect and process the center of pressure (COP) data. Three force components (F_x , F_y and F_z) along with three respective moment components (M_x , M_y and M_z) were simultaneously measured from the force platform. The signals were amplified through a six-channel AMTI model SGA6-4 amplifier. A maximum gain of 4,000 was used, with a low-pass filter of 10.5 Hz. The bridge excitation was set to 10 V. All six channels were factory calibrated. The data were collected with a sample frequency of 90 Hz.

Postural data analysis

We measured the size of and boundary around each subject's foot and the platform calibration markers in order to estimate the shape and location of the physical stability boundary during the execution of the required stances (Barin 1992). Specifically, we outlined the position of the subject's foot on the grid paper placed on the force plate. Then we measured the X - Y coordinate of the 16 landmarks along the footprint with respect to the center of the force plate coordinate system. These X - Y coordinates were ultimately used as an input into the VTC computation algorithm to define the 2-D stability boundary.

The traditional assessment of postural performances has included the center of pressure motion (COP) along the X and Y axes, standard deviation (SD), COP velocity and acceleration time series. The center of pressure at each instantaneous time point defined by the sample rate reflecting the degree of postural motion was calculated using the customized software as:

$$\text{COP}_X = -(\text{myVal} + \text{zoffset} * \text{fxVal}) / \text{fzVal} \quad (1)$$

$$\text{COP}_Y = (\text{mxVal} - \text{zoffset} * \text{fyVal}) / \text{fzVal}. \quad (2)$$

In addition, two-dimensional stability boundary measures and time series of COP instantaneous position vector along with velocity and acceleration vectors were used to compute VTC according to the procedures outlined in the Appendix (see also Fig. 1; and Slobounov et al. 1997, 1998; Haibach et al. 2007; Slobounov et al. 2008 for details).

VTC analysis: stage segmentation

Figure 2 (top) shows that under the condition where the subject was standing on one leg with closed eyes, the VTC revealed a unique dynamic pattern consisting of three sequential stages: the initial pre-falling stable stage in which the VTC fluctuates relatively smoothly, the transition stage in which the VTC fluctuates with large variance, and the falling stage in which the VTC falls to zero from the local maxima monotonously.

Computationally, the stable and transition stages were separated with a numerical method consisting of two steps described as follows. First, the time instants where the VTC increases abruptly with the first derivative larger than a selected threshold: in this study, the threshold was set to be three times the standard deviation above the mean value of all positive first derivatives. The threshold of 3-SD above the mean value is a common rule in data processing to characterize changes that are significantly different from background noise (see Chu et al. 2002 for details). Second, the selected time instants were clustered by a hierarchical clustering algorithm using MATLAB 6.5' statistics toolbox: the largest cluster is considered to be derived from the non-stationary stage. Therefore, the onset of the transition stage was defined as the first time instant of this cluster.

Our preliminary analysis revealed that VTC minimal values along with its variability progressively increased throughout the duration of the transition stage. To quantify this observation, the initial versus last 50% VTC variability during the transition stage was subjected to further statistical analysis using t test.

Identification of deflection points

The time instant where the VTC reached the local valley was identified by the Peakdet algorithm (see Elill Billauer 2008 for details). This algorithm may detect the valleys due to the

large fluctuation of the signal without picking up the local minima due to the small vibrations. The deflection points of VTC are shown in Fig. 2 as red circles.

Wavelet transform of the VTC time series

To further accentuate the accuracy of the separation of posture data into stable, transition and falling stages, a wavelet analysis of the VTC time series was implemented, similarly to EEG time–frequency decomposition. The details of VTC wavelet coefficient computation can be found in the following text (see “Time–frequency decomposition of EEG” and Fig. 3, bottom figure).

EEG recording and processing

The continuous EEG was recorded using Ag/AgCl electrodes mounted in a 64-channel Quik-Cap Electrode Helmet. The electrical activity from the scalp was recorded at 64 sites, according to the international 10–20 system (Jasper 1958). The ground electrode was located 10% anterior to FZ, linked earlobes served as references and electrode impedances were below 5 kOhms. EEG signals were recorded using a programmable DC coupled broadband SynAmps amplifier (NeuroScan, Inc., El Paso, TX.). The EEG signals were amplified (gain 2,500, accuracy 0.033/bit) with a recording range set at ± 55 mV in the DC to 70-Hz frequency range. The EEG signals were digitized at 200 Hz using 16-bit analog-to-digital converters.

The EEG data were initially processed off-line using EEGLAB 5.03 (Delorme and Makeig 2004) and Matlab open source toolbox (Mathworks, Natick, USA). The selection of EEG trials for detailed analysis was made based on synchronization between the VTC stages (stable, transitory, falling) and EEG data. After baseline normalization, these epochs were automatically screened for unique, non-stereotypic artifacts using a probabilistic function within EEGLAB. In addition, the ocular and muscular artifacts were removed from EEG signal by independent component analysis (see “Single-trial independent component analysis (ICA)” for details). Overall, these procedures allowed the removal of epochs containing signal values exceeding 3 SD and control for artifacts such as eye blinks, eye movements, heartbeats, etc.

Time–frequency decomposition of EEG

A continuous wavelet transform (CWT) was performed to reveal the evolution of EEG power within certain frequency bands over time throughout the duration of the postural trial. In the continuous wavelet transform, the power of the signal is distributed on a continuous time–frequency plane. In this study, we focused on certain frequency ranges, which were selected narrow parallel bands on the time–frequency plane along with the axis of time. The discrete wavelet transform (DWT) has discrete representations in both time and frequency domain, which is widely used in the engineering field. It is not commonly used for representation of EEG data, because it lacks good temporal and spectral resolution. Therefore, in this study the complex Morlet wavelet was used. The complex Morlet wavelet has been widely used in EEG signal analysis, because it has good time–frequency localization and its sinusoidal shape approximates the shape of the EEG signal quite well.

The continuous wavelet transform is a signal processing tool to resolve both time and scale (frequency) events and is a valuable addition to short Fourier transform (STFT). In mathematical terms for signal processing, the continuous wavelet transform of a function f is defined by:

$$\gamma(\tau, s) = \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{|s|}} \psi\left(\frac{t - \tau}{s}\right) dt \quad (3)$$

where τ represents translation, s represents scale, which is related to frequency, and ψ is the mother wavelet. $\bar{z}$ is the complex conjugate of z . In this study, the mother wavelet is a complex Morlet wavelet and has excellent accuracy both in the time and frequency domains. For computation of wavelet coefficients, we used the wavelet toolbox from MATLAB 6.5.

Single-trial independent component analysis (ICA)

The conventional EEG studies use the scalp recording research protocols. These are most likely limited by the poor spatial resolution partly due to the volume conduction effect. Moreover, the regions of interest on the scalp do not necessarily have explicit relation to the activation of brain structures directly under the skull. Moreover, EEG data processed by conventional means, especially associated with whole body postural movement, are most likely artifactual. To resolve these issues in addition to conventional FFT, we used ICA and LORETA to estimate the sources of EEG activity concomitant with execution of postural tasks under study.

ICA, a powerful data-driven mathematical tool that blindly separates the statistically independent contributions of signals was used to find temporally independent and spatially fixed EEG components (Makeig et al. 1996). According to the ICA model, the EEG signal recorded on the scalp is a mixture of the electrical potentials generated by temporally independent cerebral and artifactual bioelectrical processes (Jung et al. 2001). The summation of potentials arising from various sources in the brain, scalp and body is linear at all electrodes, and propagation delays from the sources to the electrodes are negligible. The ICA model can be written as:

$$\text{EEG}(t) = M \cdot S(t) \quad (4)$$

where $\text{EEG}(t)$ is the EEG signal recorded on the scalp with n by 1 dimension, n is the number of electrodes, $M \in R^{n \times m}$ is the mixing matrix, $S(t) \in R^{m \times 1}$ is the independent process (or brain functional property), and m is the number of independent processes. Each column of M is the topography of a corresponding independent process on the scalp. M and $S(t)$ can be estimated from $\text{EEG}(t)$ by several algorithms, such as fast ICA.

Infomax ICA was performed (EEGlab, Makeig) on the single-trial EEG data and components were obtained via minimization of mutual information among output components (Jung et al. 1999). The ICA components associated with relative brain activities were selected manually (Jung et al. 2000) according to their scalp maps and time–frequency dynamics. Specifically, we chose the independent components, the scalp maps of which were consistent with the power distribution revealed in the traditional spectrum analyses and the time–frequency dynamics were phase-locked to the behavior data.

Low-resolution tomography (LORETA)

The spatial maps associated with each ICA component were further analyzed with low-resolution tomography (LORETA) (Pascual-Marqui 1999; Pascual-Marqui et al. 1994) to locate its cerebral sources. LORETA is a tomographic technique that gives a single solution to what is known as the inverse problem of location of cerebral sources. It is based on two constraints. Specifically, it searches for the smoothest of all possible solutions, using cortical gray matter and the hippocampus of the Talairach human brain model. In recent years, the efficacy of this tomography approach has been documented in several studies (for example, see Gomez et al. 2003; Kounios et al. 2001; Mulert et al. 2001; Pizzagalli et al. 2001). The LORETA version used in this study reconstructed the sources of activation in 2,394 voxels distributed in the Talairach human brain (Pascual-Marqui 1999).

Synchronization of EEG and postural data

The EEG signal was synchronized with the COP data by using a triggering signal generated by the force platform and received by the *SynAmps* amplifier through the high-level input channel whenever the force platform starts collecting the data. The EEG data were first segmented into three epochs corresponding to the stable, transition and falling stages of VTC, respectively, and then analyzed in the frequency domain using fast Fourier transform with 50% overlap using Hanning window (signal processing toolbox, Matlab 6.5). The spectrum powers in theta (4–7 Hz), alpha (8–12 Hz), beta (14–24 Hz), and gamma (30–50 Hz) frequency bands were calculated within each portion and averaged across all relevant trials. It should be noted that these frequency bands have been traditionally used in previous movement-related EEG research.

Statistical analysis

The two-way ANOVA using the supporting leg ($n = 2$, left/right) and stage ($n = 2$; stable vs. transition) as factors was implemented to assess the statistical difference of VTC values between the stable and transition stages. The VTC in the falling stage, which has a simple pattern of decline over time reaching zero at falling, is not included in the statistical analysis due to its differential dynamics. In addition, a two-way within-subject repeated measures ANOVA using the stages ($n = 3$, stable, transition, falling) by electrode sites ($n = 64$) was applied to examine statistical differences in the power of the EEG signal (e.g., theta, alpha, beta and gamma frequency bands) associated with different stages assessed by segmentation of the VTC time series. The significance level was set at $p < 0.05$.

Results

Postural data

A representative example of VTC dynamics for right leg stance condition along with evolution of its local statistics (i.e., minimal, mean values, and SD), as well as the time–frequency decomposition of VTC is shown in Fig. 2. As seen in Fig. 2, the VTC dynamics was characterized by a consistent increase of its mean and variability prior to subjects losing their balance. Similar dynamics was observed for the left leg stance condition.

The ANOVA revealed that the main effect of VTC minimal values as a function of stage (stable vs. transition) was significant, $F(1, 11) = 12.23$, $p = 0.0062$, with the VTC minimal values longer in the transition phase. The standard deviation of the minimal VTC values was higher in the last 50% than in the initial 50% of the transition stage, $t(11) = 6.69$, $p < 0.01$. The main effect of the leg under study (right versus left) was not significant ($p > 0.05$). The duration of the transition stage ($x = 5.20$ s; $SD = 1.44$ s) prior to falling, averaged across subjects, stance conditions (right/left leg) and trials ($n = 3$), was consistently shorter [$F(1, 11) = 9.34$, $p < 0.01$], along with greater variability, [$F(11, 11) = 5.20$, $p = < 0.005$, respectively] than those for the stable stage ($x = 7.5$ s; $SD = 3.93$ s).

EEG data

The average scalp distributions of spectral power in low-theta (4–5 Hz) and -alpha (8–12 Hz) frequency bands associated with the three stages of postural stance throughout the trial duration are shown in Fig. 3. As seen in Fig. 3, the central theta power increased during the transition-to-instability stage and then significantly decreased during the falling stage. Moreover, the power of occipital alpha, initially present at both stable and transition stages, essentially reduced to non-existence during the falling stage.

ANOVA showed that the main effect of stage on EEG *low-theta* (4–5 Hz) power was significant, $F(2, 22) = 4.5$, $p < 0.05$. Post hoc analysis revealed that theta power at the transition

stage was significantly higher than that during the stable and falling stages, $p < 0.001$. The main effect of electrode site was significant, $F(61, 22) = 7.1$, $p < 0.001$, with post hoc analysis indicating that modulation of EEG low-theta power was predominantly observed at the central-frontal areas.

Similarly, the alpha power (8–12 Hz) at the occipital area persisted in the first two stages, but declined significantly at the falling stage, $F(2, 22) = 6.8$, $p < 0.01$. The main effect of electrode sites was significant, $F(61, 22) = 6.56$, $p < 0.001$, with the modulation of EEG alpha power observed predominantly at the occipital areas. The spectral analysis failed to reveal a significant difference between different stages in beta (13–24 Hz) and gamma (30–50 Hz) frequency bands.

Time–frequency analysis of independent components of EEG (ICA)

The details of the relationship between the stages of postural stance and EEG dynamics have been revealed by the analysis of time–frequency evolution of ICA components and shown in Figs. 4 and 5.

Two groups of independent components were selected according to the aforementioned criteria (see “Methods”). For the first group, the scalp maps have large values in the right and/or left central-frontal area contra-lateral to the supporting leg (right versus left) with the multiple bursts of gamma (30–50 Hz) and midline low-theta (4–5 Hz) rhythms during the transition stage. For the second group, the scalp maps have large values in the occipital region with depressed alpha rhythms during the falling stage.

LORETA results

The LORETA analysis was performed with the scalp maps associated with selected ICA components to find the generators of these maps. Only values greater than 2.5 times the standard deviation of the standardized data (in the LORETA spatial solution) were accepted as activations. As seen in Fig. 6a, b, the LORETA analysis revealed that the common source of the first group of ICA components was located at the anterior cingulate gyrus (ACC) and the limbic lobe, regardless of leg (right vs. left) stance condition. Figure 7 shows that the source of the second group of ICA components was located only at the junction of the precuneus and occipital lobe.

Discussion

There have been several previous reports suggesting that VTC may serve as an informational variable in the control of upright stance (Carello et al. 1985; Riccio 1993; Slobounov et al. 1997; Van Wegen et al. 2001). It has been speculated that VTC information in the regulation of posture could be obtained from both visual and somesthetic sensory systems (Carello et al. 1985). However, neither the role of these sensory systems in the detection and regulation of VTC, nor their neural basis have been directly examined and/or identified. Moreover, no systematic experiments have investigated the predictive values of VTC in terms of actual future instability and falls. To our knowledge, only one previous study has examined the predictive aspects of postural time to contact under external pendulum perturbations to the body (Hasson et al. 2008). In fact, VTC computation approach, using acceleration information similar to our originally proposed algorithm (Slobounov et al. 1997) has provided the best predictor of taking a step when balance was in danger.

The novel features of this study are that we have: (a) designed an experimental situation that directly induces the subjects to lose balance while performing a challenging single leg stance with eyes closed; (b) introduced a novel approach to analyze the time series of the VTC using

wavelet transform and stance segmentation procedures; and (c) examined brain responses via EEG time-locked to VTC dynamics during pre-fall stable (at the beginning of the trial), transition-to-instability and actual falling stages of the postural task. In terms of research methodology, we utilized the ICA and LORETA in addition to the original analysis of EEG (spectral analysis and spatial map).

There were no deficits in the original analysis providing the grand mean spectral power of EEG within certain frequency bands. However, the grand mean spectra in different frequency bands, although provide general information on changes in EEG power at different stages of postural stance, do not provide information regarding the evolution of EEG spectrum within and across these postural stages. The time–frequency of EEG ICA components may address this limitation in addition to providing the focal source of brain activation that cannot be obtained by using the “spatial map”.

Moreover, although ICA can decompose the recorded EEG into different brain activities and control for various artifacts, the real sources corresponding to the brain activities cannot be directly localized by the ICA spatial maps. On other hand, LORETA can localize the sources of brain activities with good accuracy, but suffers from the contamination of artifacts. By combining these tools together, we were able to localize the sources of EEG of selected brain activities without contamination effects of various artifacts. These two procedures should be considered as complementary to achieve maximal outcomes. The details in terms of the combination of ICA and LOERETA can be found in Marco-Pallarés et al. (2005).

The major behavioral finding was a systematic increase of minimal values of VTC along with enhanced variability during transition from stable to pre-fall stages that was followed by the sharp decline to zero at the time of the actual fall. The major EEG finding was that the transition to unstable postures was associated with multiple bursts of midline frontal theta and parietal gamma power, identified by the time–frequency evolution of ICA components. In addition, there was a significant reduction of alpha power at the occipital area prior to falling.

VTC dynamics

We utilized a similar approach preceding the fall to identify the stages of postural stance in both VTC and COP time series. The VTC, but not the standard COP measures, allowed us to identify both stable (at the beginning of the trial) and transition (preceding the falling) stages of postural tasks under study. Interestingly, visually neither discernable features allowing separation of stable, transition and falling stages, nor specific features of COP dynamics allowing to anticipate forthcoming falls were observed based on the analysis of COP data along the lateral (*X*-axis) or anterior–posterior (*Y*-axis) directions. Statistically, no significant differences were observed between time intervals that characterize the stable and transition phases identified by segmentation analysis using VTC time series data ($P>0.05$). This was the case for COP data along both the *X* and *Y* axes. (See Fig. 8 in support of our observations.)

The systematic increase of VTC minimal values during the transition to instability may be considered as counter-intuitive. One might expect that the progression from a stable to unstable postural configuration is associated with the increased motion of the center of pressure (Murray et al. 1975; Roberts 1995; Winter 1991; Slobounov and Newell 1994) and reduced mean and minimal time-to-contact values (Van Wegen et al. 2001, 2002, Haddad et al. 2006; Hertel et al. 2006; Hasson et al. 2008).

Although, there is still no conclusive evidence that the postural control system uses VTC information as a “control variable”, our current findings demonstrate that VTC is related to future instability and actual falls. The systematic increase of VTC minimal values (along with increased variability) during the transition to the stage of instability may be a reflection of

increased “sense of urgency” and utilization of compensatory strategies entailing the exploration of additional resources to sustain balance. In other words, while approaching the unstable stage, the postural control system may need “extra time” for exploring the perceptual–motor workspace (Kugler and Turvey 1987; Newell et al. 1989) and avoiding the collision of the center of pressure with stability boundaries and thus avoiding a fall. A systematic increase of the variability of VTC during the transition to the instability stage is consistent with the proposition that enhanced postural sway provides sensory information regarding the potential stability landscape over which postural movements are or will be occurring (Riccio 1993). The specific contribution of different sensory information to the VTC dynamics is still to be explored.

Neural basis of VTC

The EEG modulation within theta, alpha, and gamma frequency bands was time-locked with VTC time series as specified in the “Methods”. There was a significant burst of midline frontal low theta (4–5 Hz, predominantly at the Fz electrode site) during the shift from the stable stage to transition-to-instability stage, as identified by segmentation of the time series of VTC. This was followed by the reduction of theta power just preceding the actual falling. The ICA combined with LORETA techniques used to obtain spatially localized cerebral sources of EEG activity identified the anterior cingulate gyrus (ACC) as a common source of theta band. It should be noted that this common source related with the dynamics of VTC was identified regardless of whether left or right leg stance postural task was performed. This finding is consistent with those from a number of previous EEG studies demonstrating similar midline theta (e.g., Fn Theta) burst in the condition of higher cognitive load (Gevins and Smith 2000) and/or visuo-motor task complexity (Slobounov et al. 2000; Gomarús et al. 2006).

Interestingly, several recent neuroimaging studies have indicated that ACC may serve as an active monitoring system that reacts to the presence of conflict and/or performance errors (Botvinick et al. 2001; Gehring and Knight 2000). ERP studies have also suggested that medial-frontal brain activation (frontal-central electrode sites) may be involved in “high-level” error detection (Krigolson and Holroyd 2006, 2007, 2008). Collectively, our EEG theta findings complement these previous studies by indicating the involvement of ACC in monitoring postural stability. Additional research is needed to examine whether the ACC may simply provide an “alert” that a postural stance is in danger, or is specifically involved in monitoring VTC in pre-falling and transition-to-instability stages.

Another finding of interest supporting the existence of the neural basis of VTC monitoring system is that alpha modulation, which was related to the process of attention and alertness (Boiten et al. 1992; Klimesch 1999), was clearly observed as a function of the progression of the postural stages from stability to falling. The cerebral sources of this modulation were identified at the occipital lobe and the precuneus–parietal lobe junction. Clearly, depression of alpha activity in our study, as an index of general allocation of attention (Klimesch 1999), was associated with loss of balance. Attention processes have long been thought to be influenced by the level of alertness of vigilance (Posner 1993), traditionally associated with the activation of parietal cortex, and potentially may be examined via concomitant EEG/VTC measures of postural control.

Finally, modulation of EEG within the gamma (30–50 Hz) band during the transition-to-instability stage was revealed by ICA. It should be noted that traditional FFT analysis failed to identify the EEG gamma modulation, most likely due to progressive muscle fatigue and associated EMG artifact as the postural trials progressed over time. Nevertheless, the bursts of gamma activity during the transition-to-instability stage should be considered as additional evidence for the existence of “neural detectors” for postural instability. Similar multiple bursts of gamma power were documented when subjects approached the stability boundary while

performing voluntary AP sway (Slobounov et al. 2005) and/or cognitively identified unstable postures of computer-generated body models (Slobounov et al. 2006). In fact, recognition of postural instability has also induced a significant activation of the parietal–temporal junction and bilateral cerebellum, as demonstrated in our previous fMRI study (Slobounov et al. 2006). Considering the notion that increased gamma power may reflect a state of “focused arousal” (Sheer 1976) and/or “binding phenomenon” (Singer 1993; Basar et al. 1995), we suggest that the burst of gamma power shown here indeed may serve as an indication of increased effort to sustain balance prior to falling.

One may argue that the observed EEG changes are not only “posturally” related, but also may reflect changes due to prolonged exposure (e.g., fatigue) or anxiety related to loss of balance. Of course, we cannot completely rule out that muscle fatigue was a contributing factor influencing the EEG data under study. Indeed, there are a number of EEG studies, including our own findings (Johnston et al. 2001), demonstrating the differential modulation of EEG data at various stages of progressive muscle fatigue. We would also like to provide a few arguments that the observed EEG dynamics associated with task performance may directly reflect the neural basis of predicting the upcoming postural instability. First, the total time for each trial did not exceed 12 s, which is unlikely to lead to induced muscle and or mental fatigue. The necessary break between trials and randomized switch between left versus right leg stance was provided to control for fatigue. Post-study interviews indicated that the subjects reported loss of balance mostly due to the reduced ability to control “increasing body sway”, rather than due to muscle fatigue. Finally, and most importantly, the reported modulation of EEG over the trial duration was observed predominantly within low theta (midline theta, 4–5 Hz) at the frontal-central areas (Fz, Fcz electrode sites), with source localization at ACC (see ICA and LORETA). In the case of fatigue-related modulation, there should be a progressive increase of high-theta power (5–8 Hz), along with reduced parietal alpha power over time. These fatigue-related EEG changes have been reported in a number of previous studies (see Makeig and Jung 1995; Gevins et al. 1998; Trejo et al. 1995 for details).

Similarly, we cannot completely rule out the possibility of the subject’s anxiety due to loss of balance and ultimate fall. However, first, it should be noted that in this study, young and healthy physically active adults without any history of fall-related injuries were recruited. The history of previous falls, particularly in the elderly subjects, was found to be one of the serious predisposing factors to the fear of falling. Second, the subjects were wearing a harness that was demonstrated prior to experimental session as a highly reliable and protective device from hitting the ground in case of possible falls due to loss of balance. Finally, the frontal region (i.e., dorsolateral prefrontal cortex) of the brain asymmetry within the alpha band has been reported as the most validated EEG index of anxiety (see Davidson 1995, for review).

It has been shown that the brain responses to threatening stimuli are associated with reduction of prefrontal low-theta power (Aftanas et al. 2003). We observed neither modulation of EEG within the alpha band at the frontal electrode sites and localized EEG alpha source via ICA and LORETA at the central region of interest (ROI), nor reduction of central low-theta power. Instead, the power increases within the midline low-theta band, occipital alpha reduction and the parietal gamma bursts were matched with the evolution of postural instability and ultimate loss of balance. Therefore, we interpret the observed EEG changes as most likely a “posturally”, rather than a fatigue/anxiety, related phenomenon.

In summary, the findings show that a systematic increase of minimal values of VTC (and its variability) concomitant with modulation of EEG, specifically within low-theta frequency band at the frontal-central areas and alpha/gamma bands at the parietal–occipital areas, may serve as a “predictor” of future instability in posture. These EEG modulations may be interpreted as a neural underpinning of vigilance and/or increased mental alertness associated with initiation

of compensatory postural adjustments aimed at avoiding actual falls. The EEG data revealed strong relations to the VTC dynamics, but weak relations to the standard COP measures. The postural control system may monitor the predictive dynamics of VTC and initiate compensatory strategies to sustain balance during challenging postural tasks. In this view, the informational priority in postural control is the upcoming spatial and temporal dynamics to instability at the critical points of the stability boundary, rather than the positional stability at, and nearby, a postural equilibrium point that holds considerable redundancy in typical upright standing and, moreover, does not predict the time to instability at the boundary. The question of whether the threshold of “stable” VTC values and associated brain responses may vary as a function of a broader range of organism–environment–task constraints remains to be examined.

Acknowledgments

This study was supported by the NIH, NINDS grant R01NS056227-01A2. We would like to acknowledge the contribution of Elena Slobounov for conceptualization and development of the algorithm for VTC computation. We also would like to thank the reviewers for their valuable comments on our original manuscript.

References

- Aftanas LI, Pavlov SV, Reva NV, Varlamov AA. Trait anxiety on the EEG theta band power changes during appraisal of threatening and pleasant visual stimuli. *Int J Psychophysiol* 2003;50(3):205–212. [PubMed: 14585489]
- Barin K. Dynamic posturography analysis of error in force plate measurement of postural sway. *IEEE Eng Med Biol* 1992;11:52–56.
- Basar E, Basar-Eroglu T, Demiralp T, Schurmann M. Time and frequency analysis of the brain’s distributed gamma band system. *IEEE Eng Med Biol* 1995;14:400–410.
- Boiten F, Sergeant J, Geuze R. Event-related desynchronization: the effect of energetic and computational demands. *Electroenceph Clin Neurophysiol* 1992;81(4):302–309. [PubMed: 1372551]
- Botvinick M, Braver T, Barch D, Carter C, Cohen J. Conflict monitoring and cognitive control. *Psych Rev* 2001;108:624–652.
- Carello C, Kugler PN, Turvey MT. The informational support for the upright stance. *Behav Brain Sci* 1985;8:151–152.
- Chu T-M, Weir B, Wolfinger R. A systematic statistical linear modeling approach to oligonucleotide array experiments. *Math Biosci* 2002;176(1):35–51. [PubMed: 11867082]
- Davidson, R. *Brain Asymmetry*. MIT; Cambridge: 1995.
- Delorme A, Makeig S. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *J Neurosci Methods* 2004;134:9–21. [PubMed: 15102499]
- Billauer, Elill. Peakdet: peak detection using matlab. 2008. <http://www.billauer.co.il/peakdet.html>
- Field DT, Wann JP. Perceiving time to collision activates the sensorimotor cortex. *Curr Biol* 2005;15:453–458. [PubMed: 15753040]
- Gehring WJ, Knight R. Prefrontal–cingulate interactions in action monitoring. *Nat Neurosci* 2000;3:516–520. [PubMed: 10769394]
- Gevins A, Smith ME. Neurophysiological measures of working memory and individual differences in cognitive ability and cognitive style. *Cerebral Cortex* 2000;10(9):829–839. [PubMed: 10982744]
- Gevins A, Smith ME, Leong H, McEvoy L, Whitfield S, Du R. Monitoring 13 working memory load during computer-based tasks with EEG pattern recognition 14 methods. *Human Factors* 1998;40:79–91. [PubMed: 9579105]
- Goldie PA, Bach TM, Evans OM. Force platform measures for evaluating postural control: reliability and validity. *Arch Phys Med Rehabil* 1989;70:510–517. [PubMed: 2742465]
- Gomarus H, Althaus M, Wijers A, Minderaa R. The effects of memory load and stimulus relevance on the EEG during a visual selective memory search task: an ERP and ERD/ERS study. *Clin Neurophysiol* 2006;117(4):871–884. [PubMed: 16442346]

- Gomez C, Marco J, Grau C. Preparatory visuo-motor cortical network of the contingent negativity variation estimated by current density. *NeuroImage* 2003;20:216–224. [PubMed: 14527582]
- Haddad J, Gagnon J, Hasson C, Van Emmerik REA, Hamill J. Evaluation of time-to-contact measures for assessing postural stability. *J Appl Biomech* 2006;22:155–161. [PubMed: 16871006]
- Haibach PS, Slobounov SM, Slobounova ES, Newell KM. Virtual time-to-contact of stability boundaries as a function of support surface compliance. *Exp Brain Res* 2007;177(4):471–487. [PubMed: 17031683]
- Hasson CJ, Van Emmerik RE, Caldwell GE. Predicting dynamic postural instability using center of mass time-to-contact information. *J Biomech* 2008;41:2121–2129. [PubMed: 18556003]
- Hertel J, Olmsted-Kramer LC. Deficits in time-to-boundary measures of postural control with chronic ankle instability. *Gait Posture* 2007;40(2):69–70.
- Hertel J, Olmsted-Kramer LC, Challis JH. Time-to boundary measures of postural control during single leg quiet standing. *J Appl Biomech* 2006;22:67–73. [PubMed: 16760569]
- Jasper HH. The ten-twenty electrode system of the International Federation. *EEG Clin Neurophys* 1958;11:371–375.
- Johnston J, Rearick M, Slobounov S. Movement-related cortical potentials associated with progressive muscle fatigue in a grasping task. *Clin Neurophys* 2001;112:68–77.
- Judge S, Rind F. The locust DCMD, a movement-detecting neurone tightly tuned to collision trajectories. *J Exp Biol* 1997;200(16):2209–2216. [PubMed: 9320123]
- Jung, TP.; Makeig, S.; Westerifield, M.; Taunsend, J.; Courchesne, E.; Sejnowski, T. Analyzing the visualizing single-trial event-related potential. *Proceedings Of the 1998 conference on advances in neural information processing system II*; 1999. p. 118-124.
- Jung TP, Makeig S, Humphries C, Lee T, Mckeown MJ, Iragui V, Sejnowski TJ. Removing electroencephalography artifacts by blind source separation. *Psychophysiology* 2000;37:163–178. [PubMed: 10731767]
- Jung TP, Makeig S, Mckeown MJ, Bell AJ, Lee TW, Sejnowski TJ. Imaging brain dynamics using independent component analysis. *Proc IEEE* 2001;89:1107–1122.
- Klimesch W. EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. *Brain Res Brain Res Rev* 1999;29(2–3):169–195. [PubMed: 10209231]
- Kounios J, Smith RW, Yang W, Bachman P, D'Esposito M. Cognitive association formation in human memory revealed by spatiotemporal brain imaging. *Neuron* 2001;29:297–306. [PubMed: 11182100]
- Krigolson O, Holroyd C. Evidence of hierarchical error processing in the human brain. *Neuroscience* 2006;137:13–17. [PubMed: 16343779]
- Krigolson O, Holroyd C. Predictive information and error processing: the role of medial-frontal cortex during motor control. *Psychophysiology* 2007;44:586–595. [PubMed: 17437555]
- Krigolson OE, Holroyd CB, Van Gyn G, Heath M. Electro-encephalographic correlates of target and outcome errors. *Exp Brain Res* 2008;190(4):401–411. [PubMed: 18629483]
- Kugler, PN.; Turvey, M. Information, natural law, and the self-assembly of rhythmic movement: Theoretical and experimental investigations. Erlbaum; Hillsdale: 1987.
- Makeig S, Jung TP. Changes in alertness are a principal component of variance in the EEG spectrum. *NeuroReport* 1995;7:213–216. [PubMed: 8742454]
- Makeig S, Bell AJ, Jung TP, Sejnowski B. Independent component analysis of electroencephalographic data. *Adv Neural Inf Process Syst* 1996;8:145–151.
- Marco-Pallarés J, Grau C, Ruffini G. Combined ICA-LORETA analysis of mismatch negativity. *NeuroImage* 2005;25(2,1):471–477. [PubMed: 15784426]
- Martin, EJ. Unpublished master's thesis. University of Illinois; Urbana-Champaign: 1990. An information-based approach in postural measures for evaluating postural control: the role of time-to-contact with stability boundaries.
- Mataric MJ, Pomplum M. Fixation behavior in observation and imitation of human movement. *Cogn Brain Res* 1998;7:191–202.
- Mulert C, Gallinat J, Pascual-Marqui RD, Dorn H, Frick K, Schlattmann P, Mientus S, Herrmann WM, Winterer G. Reduced event-related current density in the anterior cingulate cortex in schizophrenia. *NeuroImage* 2001;13:589–600. [PubMed: 11305888]

- Murray MP, Seirewg AA, Sepic SB. Normal postural stability and steadiness: quantitative assessment. *J Bone Joint Surg* 1975;57A:510–516. [PubMed: 1141262]
- Newell, KM.; Kugler, PN.; van Emmerik, REA.; McDonald, PV. Search strategies and the acquisition of coordination. In: Wallace, SA., editor. *Perspectives on the coordination of movement*. North-Holland; Amsterdam: 1989. p. 85-122.
- Oldfield RC. The assessment and analysis of handedness: the Edinburgh inventory. *Neuropsychologia* 1971;9:97–113. [PubMed: 5146491]
- Pascual-Marqui RD. Review of methods solving the EEG inverse problem. *Int J Bioelectromagn* 1999;1:75–86.
- Pascual-Marqui RD, Michel CM, Lehmann D. Low-resolution electromagnetic tomography: a new method for localizing electrical activity in the brain. *Int J Psychophysiol* 1994;18:49–65. [PubMed: 7876038]
- Patton JL, Pai Y-C, Lee WA. Evaluation of a model that determines the stability limits of dynamic balance. *Gait Posture* 1999;9:38–49. [PubMed: 10575069]
- Pizzagalli D, Pascual-Marqui RD, Nitschke JB, Oakes TR, Larson CL, Abercrombie HC, Schaefer SM, Koger JV, Benca RM, Davidson RJ. Anterior cingulate activity as a predictor of degree of treatment response in major depression: evidence from brain electrical tomography analysis. *Am J Psychiatry* 2001;158:405–415. [PubMed: 11229981]
- Posner, MI. Interaction of arousal and selection in the posterior attention network. In: Baddeley, AD.; Weiskrantz, A., editors. *Attention: selection, awareness and control. A tribute to Donald Broadbent*. Oxford University Press; New York: 1993. p. 390-405.
- Riccio, GE. Information in movement variability about the qualitative dynamics of posture and orientation. In: Newell, KM.; Corcos, DM., editors. *Variability and motor control*. Human Kinetics; Champaign: 1993. p. 317-358.
- Ring CF, Simmons PJ. Seeing what is coming: building collision-sensitive neurons. *TINS* 1999;22:215–220. [PubMed: 10322494]
- Roberts, TDM. *Understanding balance: the mechanics of posture and locomotion*. Chapman & Hall; London: 1995.
- Rothwell, J. *Control of human voluntary movement*. 2. Chapman & Hall; London: 1994.
- Sheer, DE. Focused arousal and 40 Hz EEG. In: Knight, RM.; Bakker, DJ., editors. *The neuropsychology of learning disorders*. University Park Press; Baltimore: 1976. p. 71-87.
- Singer W. Synchronization of cortical activity and its putative role in information processing and learning. *Annual Review Physiol* 1993;55:349–374.
- Slobounov SM, Newell KM. Dynamics of posture in 3- and 5-year-old children as a function of task constraints. *Hum Mov Sci* 1994;13(6):861–875.
- Slobounov SM, Slobounova ES, Newell KM. Virtual time-to-collision and human postural control. *J Motor Behav* 1997;29:263–281.
- Slobounov SM, Moss SA, Slobounova ES, Newell KM. Aging and time to instability in posture. *J Gerontol Biol Sci* 1998;53A:B71–B78.
- Slobounov S, Tutwiler R, Slobounova E, Rearick M, Ray W. Human oscillatory activity within gamma band (30–50 Hz) induced by visual recognition of non-stable postures. *Cogn Brain Res* 2000;9:177–192.
- Slobounov S, Hallett M, Stanhope S, Shibasaki H. Role of cerebral cortex in human postural control: an EEG study. *Clin Neurophysiol* 2005;116:315–323. [PubMed: 15661110]
- Slobounov S, Wu T, Hallett M. Neural basis subserving the detection of postural instability: An fMRI study. *Mot Contr* 2006;110:69–89.
- Slobounov S, Cao C, Sebastianelli W, Slobounov E, Newell K. Residual deficits from concussion as revealed by virtual time-to-contract measures of postural stability. *Clin Neurophysiol* 2008;119:281–289. [PubMed: 18068428]
- Solstad T, Boccaro C, Kropff E, Moser MB, Moser E. Representation of geometric borders in the entorhinal cortex. *Science* 2008;322:1865–1868. [PubMed: 19095945]
- Sun H, Frost BJ. Computation of different optical variables of looming objects in pigeons nucleus rotundus neurons. *Nat Neurosci* 1998;1:296–303. [PubMed: 10195163]

- Trejo LJ, Kramer AF, Arnold JA. Event-related potentials as indices of display-monitoring performance. *Biol Psychol* 1995;40:33–71. [PubMed: 7647186]
- Van Wegen EEH, Van Emmerik REA, Wagenaar RC, Ellis T. Stability boundaries and lateral postural control in Parkinson's disease. *Mot Contr* 2001;3:254–269.
- Van Wegen EEH, Van Emmerik REA, Riccio GE. Postural orientation: age-related changes in variability and time-to-boundary. *Hum Mov Sci* 2002;21:61–84. [PubMed: 11983434]
- Winter, DA. Biomechanics and motor control of human movement. 2. Wiley; New York: 1991.

Appendix

It is important to note that both the conceptualization of the time-to-contact approach and computational differences may be the major reasons for discrepancies among recently published studies. In short, the one-dimensional constant velocity Lee' tau method (originally developed for posture by Riccio 1993), adopted by Hertel et al. (2006) and Van Wegen et al. (2002), is conceptually different from our originally proposed virtual time-to-contact (VTC) method (Slobounov et al. 1997). Overall, unlike Lee's tau method, the VTC takes into account the instantaneous position, velocity, and acceleration vectors with respect to two-dimensional stability boundary in computation of VTC. The use of different methodologies makes interpretation of time-to-contact data and comparisons between studies less than straightforward (Haddad et al. 2006). However, as mentioned in the "Discussion", the VTC computation approach, using acceleration information similar to our originally proposed algorithm (Slobounov et al. 1997, outlined below), has provided the best predictor of taking a step when balance is in danger (Hasson et al. 2008).

VTC in this study was defined as the time taken by an object to reach the stability boundary, if the object were to move from the current position on its real trajectory, with instantaneous initial conditions and constant acceleration, along the virtual trajectory. To calculate the VTC value for each instantaneous measured position of the center of pressure (the object in our case), the real time was stopped at a current moment (t_i) and the virtual motion of the object with constant acceleration was simulated. The resultant force, as well as acceleration $\vec{a}(t_i)$, was considered to be constant while the object moved along its virtual trajectory from the current initial position $\vec{r}(t_i)$ with instantaneous initial velocity $\vec{v}(t_i)$, until it collided with the stability boundary (calculated here on a functional stability boundary as described earlier).

The position vector of the center of pressure on the virtual trajectory $\vec{\rho}_i(\tau)$ started at the moment t_i as a function of time was obtained by double integration of constant acceleration $\vec{a}(\tau) = \vec{a}(t_i)$ with respect to virtual time parameter τ ,

$$\vec{\rho}_i(\tau) = \vec{r}(t_i) + \vec{v}(t_i)\tau + \vec{a}(t_i)\frac{\tau^2}{2}. \quad (5)$$

The same equation is written in terms of x and y components of the center of pressure with respect to the reference frame attached to the force platform as:

$$x_i(\tau) = r_x(t_i) + v_x(t_i)\tau + a_x(t_i)\frac{\tau^2}{2}, \quad (6)$$

$$y_i(\tau) = r_y(t_i) + v_y(t_i)\tau + a_y(t_i)\frac{\tau^2}{2} \quad (7)$$

where:

- $r_x(t_i)$ and $r_y(t_i)$ are components of instantaneous initial position vector;
- $v_x(t_i)$ and $v_y(t_i)$ are components of instantaneous initial velocity vector;
- $a_x(t_i)$ and $a_y(t_i)$ are components of instantaneous initial acceleration vector.
- The virtual trajectory has a parabolic shape if the initial velocity and acceleration vectors are not co-linear. However, the virtual trajectory is linear if the initial velocity is linear.

Each boundary segment must be checked for crossing with the current virtual trajectory. The components of the position vector for crossing point (x_c, y_c) were determined by:

$$x_c(\tau) = r_x(t_i) + v_x(t_i)\tau + a_x(t_i)\frac{\tau^2}{2} \quad (8)$$

and

$$y_c(\tau) = r_y(t_i) + v_y(t_i)\tau + a_y(t_i)\frac{\tau^2}{2}. \quad (9)$$

For the case when the boundary segment had a vertical orientation, the value $x_c = x_b$ was substituted into Eq. 4 to obtain the value of the time parameter for the crossing point. For the case when the boundary segment had a horizontal orientation, the value $y_c = y_b$ was substituted into Eq. 5.

For all other possible orientations of the boundary line segment with two distinct end points, (x_1, y_1) and (x_2, y_2) , the dependency between components of a crossing point is determined by:

$$y_c = y_1 + s(x_c - x_1) \quad (10)$$

where

$s = (y_2 - y_1)/(x_2 - x_1)$ is the slope.

In this case, Eqs. 4 and 5 should substitute y_c and x_c , respectively, in Eq. 10 and form the resulting quadratic equation,

$$A\tau^2 + B\tau + C = 0 \quad (11)$$

where:

$$\begin{aligned} A &= [a_y(t_i) - sa_x(t_i)]/2; \\ B &= [v_y(t_i) - sv_x(t_i)]; \\ C &= [(r_y(t_i) - y_b) - s(r_x(t_i) - x_b)]. \end{aligned}$$

In all three cases, the possible values of parameter τ were obtained by solving the corresponding resulting quadratic equation. If the equation did not have a solution, the infinity value was

assigned to parameter τ . For each measured position of the center of pressure, this procedure was repeated until the time parameters for all possible crossing points of the simulated virtual trajectory with all boundary segments were computed. Then the minimum positive time parameter τ associated with the first crossing point was assigned to *VTC*. Please note that infinity is a legitimate value for *VTC*, which means that contact will never occur, and that the zero *VTC* value means that the object is in contact with the boundary.

Fig. 1.

Schematic representation of the virtual time-to-contact (VTC) calculation with respect to geometric stability boundary during a single leg stance. Some virtual trajectories projected from two representative initial centers of pressure coordinate points are outlined. The *dotted line* represents the center of pressure motion during a single trial. The *dashed line* represents the virtual trajectories at point initial positions of the center of pressure. Note, the virtual trajectory has a parabolic shape if the direction of the initial velocity and the acceleration vectors are not colinear. However, the virtual trajectory is linear, if the initial velocity and initial acceleration vectors have the same direction, or either of them is equal to zero

Fig. 2.

Dynamics of VTC time series including: **a** the stages of balance trial identified by segmentation analysis (see “Methods”); **b** evolution of minimal values of VTC; **c** evolution of mean values of VTC; **d** SD of VTC; time–frequency plot of VTC obtained by means of Morlet wavelet transform. *Red vertical lines (top)* outline the transition-to-instability phase. *Red circles (top figure)* represent deflection points

Fig. 3. The topographic distributions of the grand mean spectral energy in low-theta (4–5 Hz) and -alpha (8–12 Hz) frequency bands in three stages, generated by the codes in EEGLAB toolbox. The figures are scaled within each frequency band for better comparison

Fig. 4.

A representative example of the first group ICA components **a** right leg and **b** left leg supporting condition. From *top to bottom* VTC time series; ICA components; time–frequency evolution of ICA component in gamma and theta bands. The *vertical red lines* indicate the transition between different stages of a postural task

Fig. 5.

A representative example of the second group ICA components: right leg supporting condition. From *top to bottom* VTC time series; ICA components; time–frequency evolution of ICA component in alpha band. The *vertical red lines* indicate the transition between different stages of a postural task

Fig. 6.

Brain sources of associated scalp maps of the first group ICA components computed by LORETA (*red areas* show LORETA standardized values 2.5 times greater than the standard deviation in the LORETA spatial solution). **a** Right leg stance condition; **b** left leg stance condition. Note, the common source of the first group of ICA components was located at the cingulate gyrus and the limbic lobe (Brodmann's area # 24)

Fig. 7.

Brain sources of associated scalp maps of the second group ICA components computed by LORETA (*red areas* show LORETA standardized values 2.5 times greater than the standard deviation in the LORETA spatial solution). Note, the source of the second group of ICA components was located at the junction of the precuneus and the parietal lobe (Brodmann's area # 7). Only the right leg stance condition is shown, since no differences were observed between leg conditions

Fig. 8.

Representative example of the time series of the center of pressure (COP) data along the lateral direction, X **(a)**; and anterior–posterior direction, Y **(b)** axes. Standard deviation (SD) of COP and time–frequency plots of COP time series were obtained by means of Morlet wavelet transform. Note, no discernable features allowing separation of stable stage and transition to instability leading to falling can be observed