

Multiple timescales in postural dynamics associated with vision and a secondary task are revealed by wavelet analysis

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Chagdes, J., Rietdyk, S., Haddad, J.M., Zelaznik, H.Z., Raman, A, Rhea, C.K., & Silver, T.A. (2009). Multiple time scales in postural dynamics associated with vision and a secondary task are revealed by wavelet analysis. *Experimental Brain Research*, 197, 297-310.

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Abstract:

Discrete wavelet analysis is used to resolve the center of pressure time series data into several timescale components, providing new insights into postural control. Healthy young and elderly participants stood quietly with their eyes open or closed and either performed a secondary task or stood quietly. Without vision, both younger and older participants had reduced energy in the long time-scales, supporting the concept that vision is used to control low frequency postural sway. Furthermore, energy was increased at timescales corresponding to closed-loop (somatosensory and vestibular) and open-loop mechanisms, consistent with the idea of a shift from visual control to other control mechanisms. However, a relatively greater increase was observed for older adults. With a secondary task a similar pattern was observed—increased energy at the short and moderate timescales, decreased energy at long timescales. The possibility of a common strategy—at the timescale level—in response to postural perturbations is considered.

Keywords: Postural dynamics, Wavelets, Nonlinear dynamics, Dual-task Vision, Aging, Timescales

Article:

Introduction

Postural sway about an upright equilibrium is maintained by several neuromuscular feedback loops and open-loop control; these mechanisms continually compensate for internal and external disturbances. Analysis of postural sway using mathematical models and statistical tools is of considerable interest because, in principle, it can be used to identify changes in the neuromuscular responses that occur with aging, disease, or as individuals perform various tasks (i.e. manual or cognitive tasks). This holds great potential for the development of “simple” clinical tests that can be used in the early detection of neuromuscular impairments and to quantify changes in balance control mechanisms.

Typically, postural sway is quantified by the magnitude of center of pressure (CoP) movement over time (Błaszczyk et al. 2007; Suarez et al. 1999, 2001, 2007; Laufer et al. 2006; Rama-Lopez et al. 2004). Standard Fourier measures of the CoP are then used to quantify changes in CoP dynamics. For example, the mean power frequency (MPF) of the CoP signal has been observed to increase when the eyes are closed (e.g. Davis et al. 2009), reflecting faster changes in the CoP displacement. Other researchers have quantified differences in Fourier spectra of the CoP signal (e.g. Gauchard et al. 1999; Perrin et al. 2002) or measures of central tendency and/or spectral dispersion (e.g. Dault and Frank 2004; Laufer et al. 2006; Williams et al. 1997), although some have quantified the response at various frequency ranges (e.g. Gepner and Mestre 2002; Querner et al. 2000). These measures are used regularly, and they may be useful as biomarkers of declines in postural control (e.g. Williams et al. 1997). Inferences regarding postural stability and control are then made based on the amount of CoP movement; larger CoP movement implies less stable balance and vice versa. However, recent research suggests that increased CoP movements do not necessarily indicate an impending postural destabilization

(Carello and Turvey 1985; Dault and Frank 2004; Huxhold et al. 2006; Riccio 1991; van Emmerik and van Wegen 2002). This is because postural movements generate visual, proprioceptive, and vestibular sensory feedback. CoP movements can be exploratory; they provide information to the individual about the environment in which they are moving (e.g. compliancy of the support surface) (Gibson 1979; Riccio 1991; Riccio and Stoffregen 1988). Consequently, any minimization of postural sway deprives the individual of these exploratory experiences and ultimately makes the postural system less able to effectively respond to a dynamically unfolding environment. Therefore, better measures of postural sway are needed that can reliably characterize postural sway.

In order to address the limitations inherent in linear measures of sway (that only examine the magnitude of postural movements), recent studies are beginning to use time-dependent non-linear measures to analyze CoP data. For example, Lyapunov exponents (Collins and DeLuca 1994; Donker et al. 2007; Ladislao and Fioretti 2007; Roerdink et al. 2006), sample entropy (Donker et al. 2007; Roerdink et al. 2006), approximate entropy (Cavanaugh et al. 2005) and recurrence quantification analysis (Haddad et al. 2008; Kinsella-Shaw et al. 2006; Schmit et al. 2006) have been used to quantify the complex behavior of the CoP. These researchers have inferred that postural systems that exhibit non-linear complex behaviors may be more stable, flexible, and adaptable compared to postural systems that exhibit more regular/less chaotic dynamics (see Riley et al. 1999).

Although non-linear time-dependent measures have proven to be a valuable tool in assessing the health of the postural system (Vaillancourt and Newell 2002), they do not provide information regarding the several timescales that constitute the CoP signal (Collins and DeLuca 1993). Collins and DeLuca (1993) found that the CoP position migrates within the bounds of the base of support and is controlled by both long (closed-loop) and short (open-loop) timescale processes that appear to change with age (Collins et al. 1995). Similarly Duarte and Zatsiorsky (2001); Zatsiorsky and Duarte (1999, 2000); Zatsiorsky and King (1998) suggest the presence of two timescales in the “rambling and trembling” decomposition of CoP motion. Such studies have focused on extracting only two timescale components (one fast and one slow) in the CoP signal.

Wavelet decomposition is a useful tool in the analysis of postural control and stability because several neuromuscular feedback loops act at different discrete timescales and are not visible during the entire time series but instead are intermittent. Wavelets can examine many different time-scales at different time instants (Addison 2002; Misiti et al. 1996) and provide useful results to identify changes in posture control due to aging, development, and disease. Wavelets can be used in many different ways to characterize postural dynamics, of which only a handful have been explored thus far. Wavelet analyses have been used to examine coherence values between motion of a moving room and postural adjustments (Slobounov et al. 2007). Wavelet transforms have been applied as continuous (Suarez et al. 1999, 2001) or discrete (Bertrand et al. 2001; Khandoker et al. 2007) to explore wavelet coefficients (WCs) of CoP trajectories. In addition, discrete wavelet transforms have been used to decompose CoP trajectories in the time domain at multiple timescales (Uetake et al. 2004); however, few conclusions were drawn from the decompositions. Discrete wavelet transforms have been used to examine the variance over time of WCs at specific timescales (Turner et al. 2000). Using discrete wavelet transforms the multi-fractal spectra of the CoP signal has been quantified to describe the “smoothness” of the signal and the variety of fractal structures (Morales and Kolaczyk 2002; Shimizu et al. 2002; Turner et al. 2002; Zhu et al. 2007). Thus, the CoP signal is amenable to wavelet analysis. We propose to further these analyses to answer the following questions: What can be learned from decomposing the CoP data in the time domain into several timescales? Which timescale is dominant in CoP data? How can timescale content be quantified in CoP data? Which timescales are most sensitive to postural manipulations such as closing of eyes, timing task, and age? Can the dominant or sensitive timescales be correlated to underlying closed-loop (somatosensory and vestibular) and open-loop mechanisms of postural stability? All these are important and relevant, yet unaddressed questions that can be answered using wavelet analysis.

In this article, we build upon prior wavelet-related postural research in order to: (a) espouse a method using the discrete wavelet transform to explore and quantify the different timescales in CoP data and (b) increase our understanding of postural control mechanisms through the application of discrete wavelet transforms. We

quantify the effects of commonly used postural manipulations (age, vision, and concurrent task performance) at multiple timescales. Aging and visual information have been shown to be powerful determinants of postural behavior (Guerraz and Bronstein 2008; Stelmach et al. 1990; Woollacott and Velde 2008) while concurrent timing tasks require cerebellar processes (Ivry et al. 2001; Zelaznik et al. 2008). Given that postural control also requires cerebellar processes, it is expected that the joint task of standing in combination with performing a timed tapping task should produce changes in the underlying structure of postural movements, which should be discernible with a fine grained wavelet analysis.

Methods

Ground reaction forces and moments were recorded while an individual stood on a force plate (AMTI, Watertown, MA, USA). These data were sampled at 200 Hz and used to calculate CoP time series (Winter 1995). The data were not filtered. CoP data were collected for 11 young subjects (5 males, 6 females; age range 19–30 years; mean 21.9 years) and 6 elderly subjects (4 males, 2 females; age range 67–72 years; mean 69.8 years). Each subject stood on a force plate in each of four conditions: quiet standing with eyes open, quiet standing with eyes closed, finger tapping with eyes open, and finger tapping with eyes closed. Standing still required the subjects to stand quietly on a force plate with their feet together for 70 s. The finger tapping task required the subject to stand on the force plate, and hold their arms so their forearms were parallel to the ground. In tapping, participants were required to flex and extend both index fingers at the metacarpophalangeal joint so that each finger reached its max flexion coincident with the beep of a metronome (set to 2 Hz). When the metronome engaged, the subjects entrained their movements to it. After 16 beeps of the metronome (8 s) the metronome disengaged and the subject continued to tap as though the metronome was still engaged, for a duration of 70 s. Tapping movements were performed “in the air” such that no tactile information from an external source was provided (see Lackner et al. 1999). In all conditions, subjects wore blinders that removed visual information from the lower hemisphere of the visual field. Thus, the participant could not see their hands and ground immediately below them. Each subject completed three trials for each of the four postural tasks (Fig. 1).

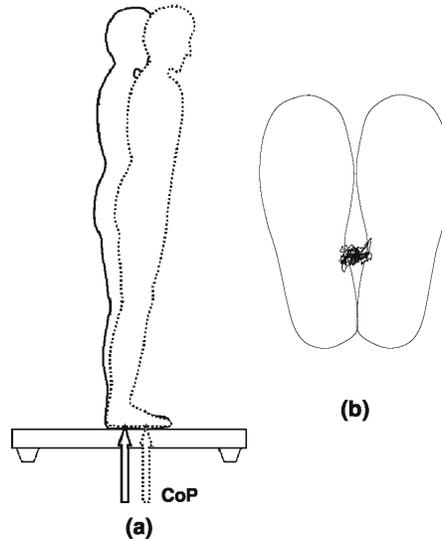


Fig. 1 **a** Side view of human at two positions of sway with the resulting center of pressure represented as the *arrows* and **b** bird's eye view of center of pressure trajectory near the stability boundary

Background on wavelet transform analysis

Mathematically, the continuous wavelet transform is a convolution of the time series signal with wavelets of various scales and translations (Addison 2002),

$$T(a, b) = \int_{-\infty}^{\infty} x(t) \psi_{a,b}^*(t) dt, \quad (1)$$

where $x(t)$ represents the time series data, the function $\psi_{a,b}(t)$ represents a “wavelet” at timescale “ $t_a = \frac{2^a}{f_{sampling}}$ ” and time instant “ b ”, $f_{sampling}$ being the sampling frequency of the signal, and the symbol “ $*$ ”

represents the complex conjugate of a function. $T(a,b)$ then is the “wavelet coefficient” (WC) at timescale t_a and time instant b . These wavelets $\psi_{a,b}(t)$ are also known as “child wavelets” and are derived from a basis function referred to as the “mother wavelet,” $\psi(t)$ (Addison 2002),

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right). \quad (2)$$

A child wavelet then essentially is a function of time of timescale t_a and localized near the time instant b . There are a number of mathematical requirements that wavelets must satisfy (Addison 2002; Misiti et al. 1996), and the commonly used wavelets such as Haar, Daubechies, Biorthogonal, and Discrete Meyers satisfy these criteria, each representing a specific signal localized in time.

The continuous wavelet transform converts a real time series signal $x(t)$ into a real two dimensional space (a,b) by using Eq. 1 to calculate the WCs $T(a,b)$ at each timescale t_a and time instant b . This continuous spectrum of WCs was computed using MATLAB for the anterior–posterior CoP time series data for a 23-year-old male in the quiet standing with eyes closed condition. The results can be seen in Fig. 2b. Details of the WCs at timescales 1.8 and 0.8 s are shown in Fig. 2c. Figure 2 clearly shows that short time-scale (say 0.8 s) corrections to the posture take place intermittently and often at different time instants compared to the longer timescale corrections (for example at 1.8 s). By way of comparison, a Fourier transform of the same time series data would average frequency components over the signal, and thus would not be able to discriminate the different timescale corrections that can occur at different time instants.

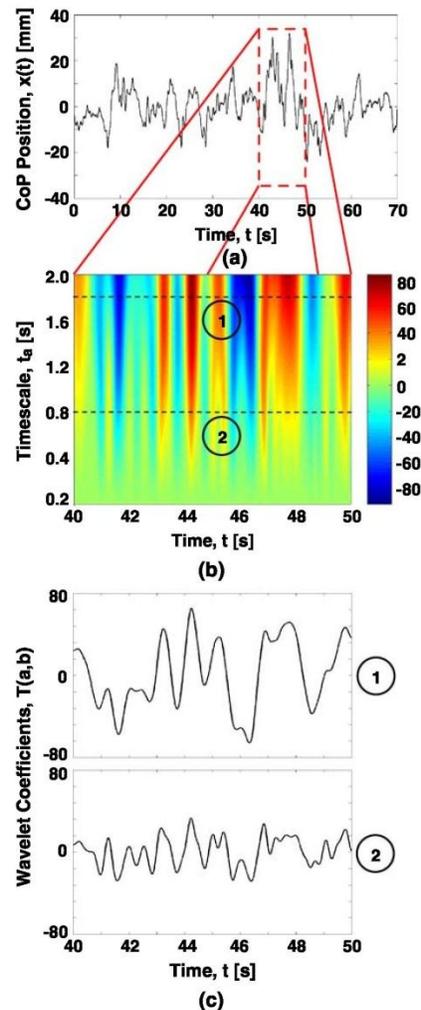


Fig. 2 a 70-s time series signal of the anterior–posterior CoP trajectory (mm) for a 23-year-old male (subject 14) while in the quiet standing with eyes closed condition and **b** magnitude of the WCs plotted (see color scale) as a function of timescale (seconds) and time instants (seconds) of the time series signal in **a** from 40 to 50 s using a continuous wavelet transform with the Discrete Meyer wavelet. **c** Details of the time evolution of the WCs from **b** at a timescale of 1.80 s and evolution of the WCs from **b** at a timescale of 0.8 s

As useful as the continuous wavelet transform is in identifying the important timescales and the WCs in the time series data, it cannot be used directly to reconstruct the signal at specific timescales. For this reason, the decomposition of a signal requires a discrete wavelet transform. This is accomplished by determining the WCs in the same manner as described earlier; however, both the timescale a and time instant b become discrete (a and b are now integers). In this paper, we follow the commonly used prescription for discrete wavelet transform scales (Addison 2002),

$$a = 2^j \text{ and } b = 2^j k, \quad (3)$$

where $j = 1, \dots, J$ are now the discrete levels of timescales at which the signal can be represented so that the timescale range at level j is $t_j = \left\{ \frac{2^{2(j-1)}}{f_{\text{sampling}}}, \frac{2^{2j}}{f_{\text{sampling}}} \right\}$ and $k = 0, \dots, K(j)$ are the discrete locations $K(j) = \text{floor} \left(\frac{N-2^j}{2^j} \right)$, where “*floor*” stands for the floor function and rounds down to the next integer. The discrete wavelet transform converts a real time series signal $x(t_i)$ sampled at discrete time instants t_i into a real two dimensional space (j, k) by using Eqs. 1 and 3 to calculate the WCs, $T(j, k)$, at each discrete level j and discrete location k .

WCs at each of the discrete levels of timescales can be thought of as “detail WCs” and can be used in the reconstruction of the time series signal at the specified level resulting in a “detail” time series signal (Addison 2002),

$$d_j(t) = \sum_{k=0}^{K(j)} T(j, k) \psi_{j,k}(t). \quad (4)$$

Similar to determining “detail WCs” one can determine “approximation WCs” (Addison 2002),

$$S(j, k) = \int_{-\infty}^{\infty} x(t) \phi_{j,k}(t) dt, \quad (5)$$

where $\phi_{j,k}(t)$ is a scaling function of a wavelet which is associated with the smoothing of the signal (Addison 2002) and $S(j, k)$ then is the “approximation WC” at level j and location k . These scaling functions $\phi_{j,k}(t)$ derive from a basis function referred to as the “father wavelet,” $\phi(t)$ (Addison 2002),

$$\phi_{j,k}(t) = \frac{1}{\sqrt{2^j}} \phi \left(\frac{t - 2^j k}{2^j} \right). \quad (6)$$

The “approximation” time series signal can then be constructed as (Addison 2002),

$$a_j(t) = \sum_{k=0}^{K(j)} S(j, k) \phi_{j,k}(t). \quad (7)$$

This discrete spectrum of WCs was computed using MATLAB for the anterior–posterior CoP time series data for the same 23-year-old male in the quiet standing with eyes closed condition. The reconstruction of the “detail” and “approximation” time series signals can be seen in Fig. 3. One can see that the CoP time series is composed of CoP motion at multiple timescales.

One interesting application of decomposing the CoP data into signal components at different timescales is shown in Fig. 4. The time series data at different timescales for the 23-year-old male in the quiet standing with eyes closed condition was differentiated, and the CoP velocity and position are simultaneously plotted in a state space or phase diagram for the time series data presented in Fig. 2. Interestingly at levels 10–12 the CoP features large loops in phase space suggesting significant low frequency, large amplitude oscillations, possibly caused by closed-loop control. This result is consistent with the notions of Collins and DeLuca (1993) or the rambling idea of Zatsiorsky and Duarte (1999, 2000). In addition, at levels 9 and below the CoP exhibits loops, which suggest high frequency, short amplitude oscillation possibly caused by open-loop control explained by Collins and DeLuca (1993) or the trembling of Zatsiorsky and Duarte (1999, 2000). While these prior works quantify two timescales in the CoP signal, the present approach is able to extract the CoP data at multiple time scales.

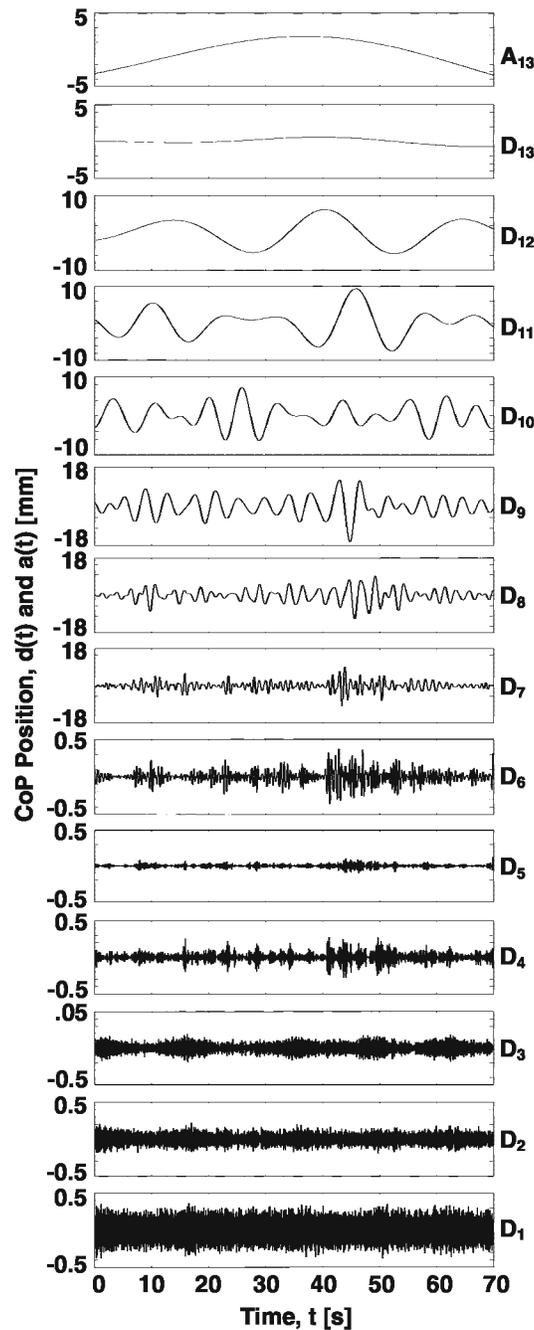


Fig. 3 A 13-level discrete wavelet transform decomposition in time domain of 70-s time series signal of the anterior–posterior CoP trajectory for a 23-year-old male (subject 14) while in the quiet standing with eyes closed condition

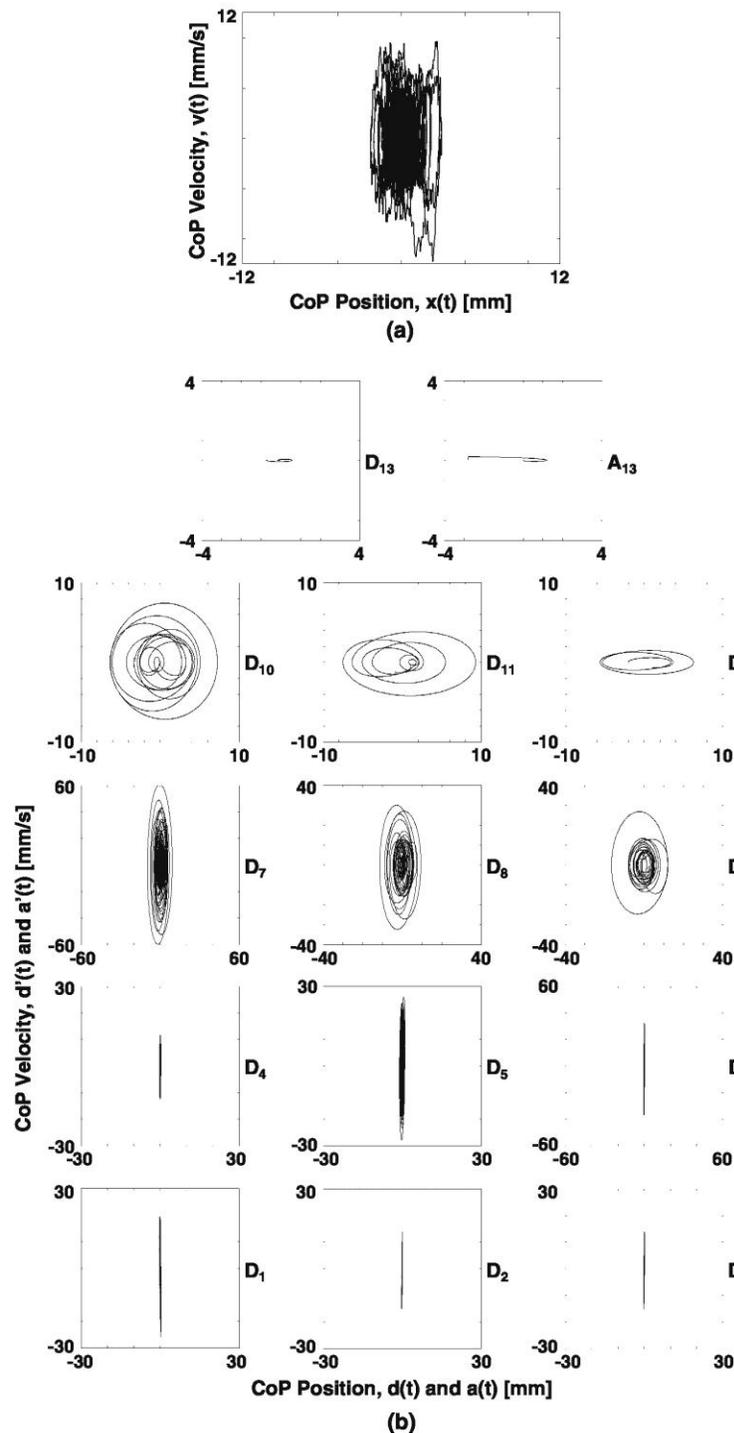
Data analysis

One advantage of decomposing the CoP signals into different discrete timescales is that the energy content at each timescale can be easily evaluated. For example the energy content at the level “ j ” can be expressed in terms of the detail WCs at that scale [$E(j)$, see Eq. 8 in Appendix 1]. The total energy of signal is calculated by summing the energy over all J levels, and the energy content at each scale can be expressed as a percentage of the total energy of the signal [$E\%(j)$, see Eqs. 9 and 10 in Appendix 1]. An example of the percentage of energy content at each timescale for the anterior–posterior CoP trajectory of a 23-year-old male is shown for the quiet standing with eyes open (SEO) condition (Fig. 5a) and quiet standing with eyes closed (SEC) condition (Fig. 5c) (average and standard error calculated for three trials).

The vision effect was examined by comparing changes in postural response between the quiet standing with

eyes open and quiet standing with eyes closed conditions by defining the energy percentage change between these conditions for each subject [$\Delta E_{EYE}\%(j)$, see Eq. 11 in Appendix 2, 3] (see example for same subject in Fig. 5e). Similarly, the energy percentage change for tapping was calculated using the quiet standing eyes open versus standing while tapping (also with eyes open) [$\Delta E_{TAP}\%(j)$, see Eq. 12 in Appendix 2, 3].

Fig. 4 **a** A state space plot, and **b** a 13-level state space plot using discrete wavelet transform decomposition of 70-s time series signal of the anterior-posterior CoP trajectory for a 23-year-old male (subject 14) while in the quiet standing with eyes closed condition

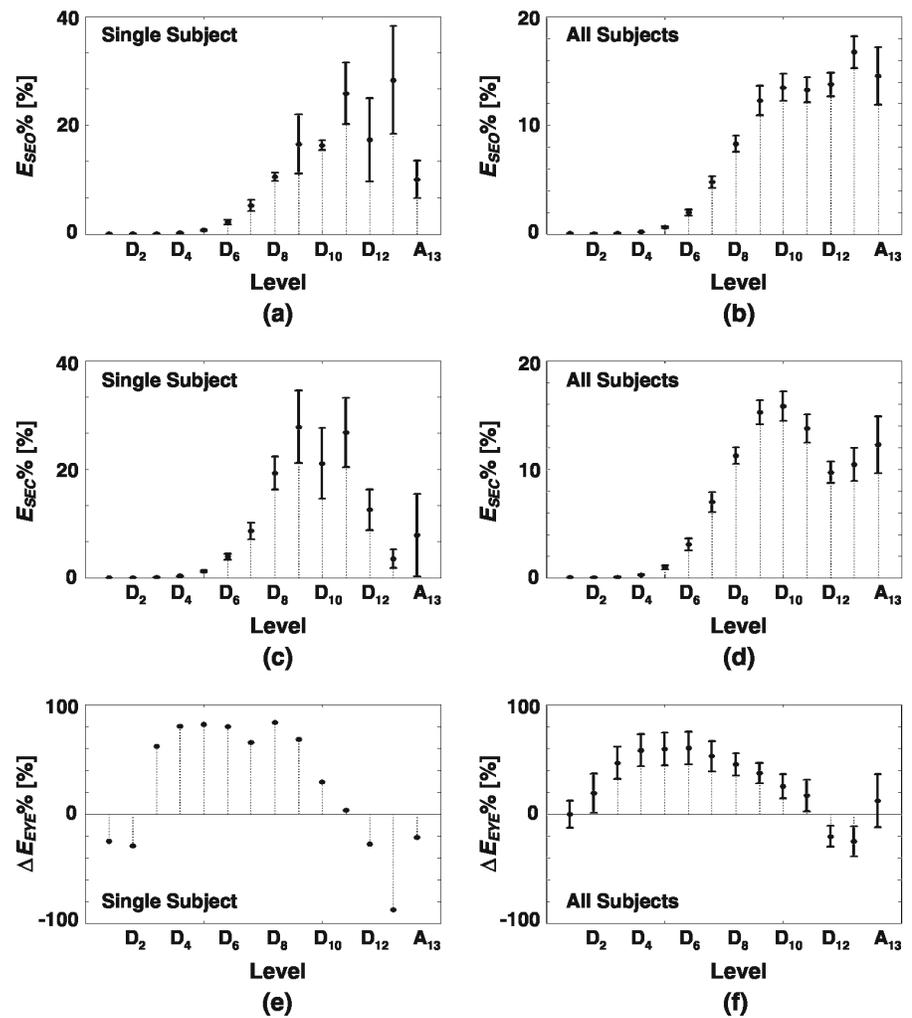


Results

Energy content during quiet standing

The percentage of energy content was very low at the shortest timescales and gradually increased at the moderate timescales and leveled off at the moderate to long time-scales (Fig. 5b); a dominant timescale was not observed. When the eyes were closed, a reduction in the longest timescales is visible in the data (Fig. 5d), but shorter timescales appear relatively unchanged. When expressed as a percentage change (Eq. 11) from eyes open to eyes closed, the decrease at the longer timescale is quantified as a negative value (Fig. 5f). However, it becomes apparent that there was also a relatively large increase in the short and moderate timescales (Fig. 5f).

Fig. 5 Average energy percentage with standard error for 13-level discrete wavelet transform decomposition of three trials of 70-s time series signals of the anterior–posterior CoP trajectory for a 23-year-old male (subject 14) while in **a** quiet standing with eyes open condition, **c** quiet standing with eyes closed condition **e** energy percentage change of **a** and **b**, and all subjects while in **b** quiet standing with eyes open condition, **d** quiet standing with eyes closed condition and **f** average energy percentage change of all subjects



Effects of vision and age

A positive energy percentage change as a function of vision [$(\Delta E_{EYE}\%(j))$] indicates that there was more energy at that timescale when quiet standing with eyes closed versus eyes open and vice versa (Eq. 11). In the young adults standing with eyes closed, energy content decreased in the long timescales ($j = 12, 13$, corresponding to a range of timescales 0.012–0.049 Hz) and energy content increased at the shorter timescales ($j = 1, \dots, 11$ corresponding to 0.049–100 Hz) (Fig. 6a). Older adults had a similar pattern (Fig. 6c), although the magnitudes are larger for older adults. The energy percent change for older and younger adults is plotted in Fig. 6e to facilitate comparison; the older adults have larger changes in energy at all timescales.

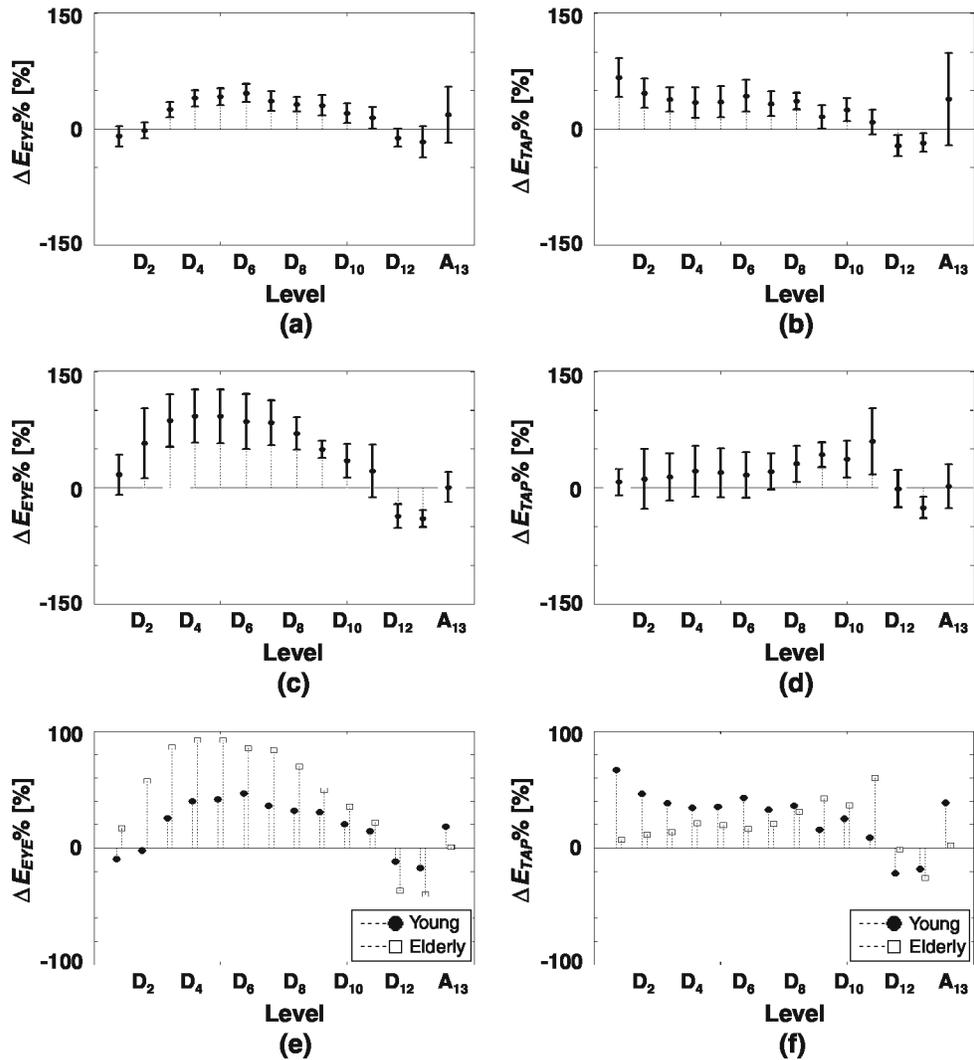
Effects of timing tasks and age

When young adults tapped their fingers at 2 Hz while standing with their eyes open, energy decreased in the long timescales ($j = 12, 13$, corresponding to 0.012–0.049 Hz) and energy content increased at the shorter timescales ($j = 1–11$, corresponding to 0.049–100 Hz) (Fig. 6b). Older adults had a similar pattern (Fig. 6d). The magnitudes were similar across young and older adults, although there was a tendency for older adults to have slightly less change in energy at the shorter and longest timescales (Fig. 6f), with a greater change in energy at moderate timescales ($j = 9–11$) (Fig. 6f).

Fourier analysis

To provide a comparison of wavelet to Fourier analysis of the CoP data, the time histories of various subjects in all four conditions were analyzed using discrete Fourier transform (DFT) in MATLAB by sampling the CoP data at 200 Hz and down sampling to 100 Hz. As one typical example considers the anterior–posterior CoP time series data for a 23-year-old male in the quiet standing with eyes closed condition. As shown in Fig. 7, no key frequencies were observed in the CoP Fourier spectrum.

Fig. 6 Average energy percentage change with standard error for 13-level discrete wavelet transform decomposition of 70-s time series signals of the anterior–posterior CoP trajectory of **a** the vision effect of young subjects, **b** tapping effect of young subjects, **c** vision effect of elderly subjects, **d** tapping effect of elderly subjects, **e** age comparison for vision effect analysis and **f** age comparison for the tapping effect analysis



Wavelet Type

The change in energy percentage at each timescale for three different wavelet functions, Haar, Discrete Meyer, and Biorthogonal 1.3 (Misiti et al. 1996) are shown in Fig. 8.

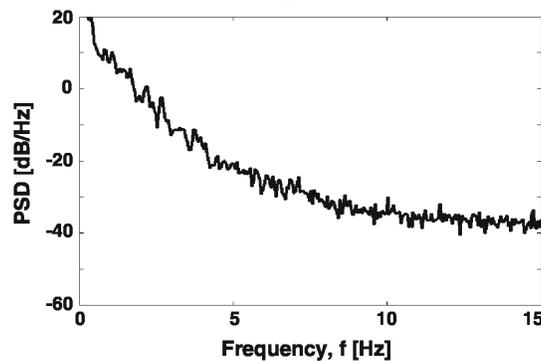


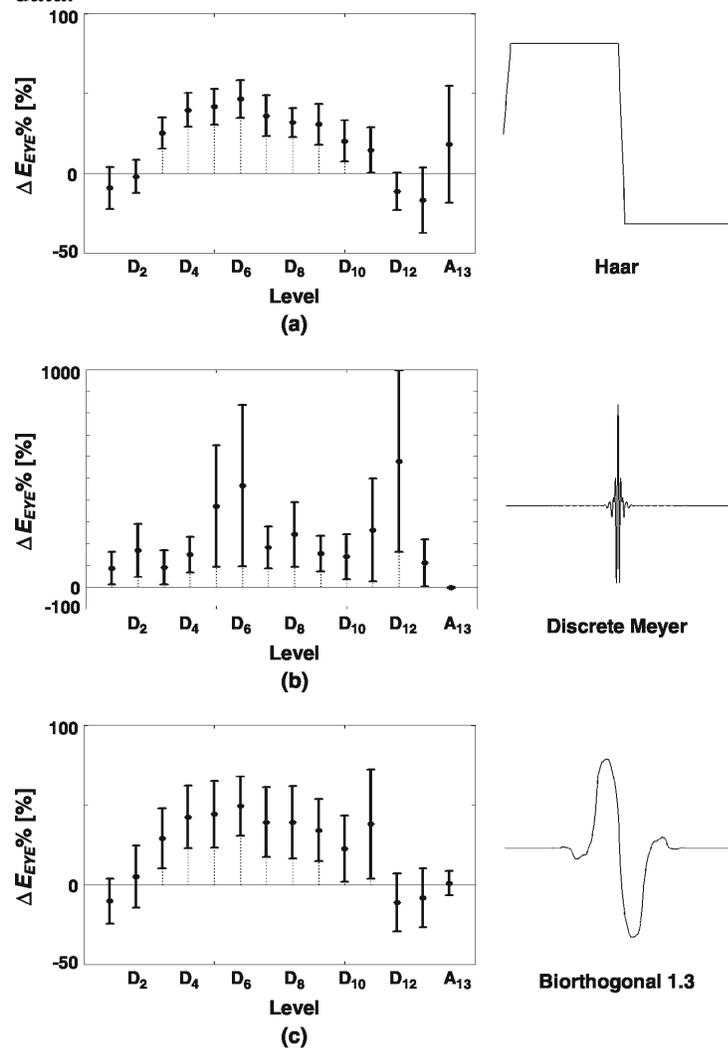
Fig. 7 DFT of 70-s time series signal of the anterior–posterior CoP trajectory for a 23-year-old male (subject 14) while in the quiet standing with eyes closed condition

Discussion

The contribution of different sensory systems to postural control is not yet well understood. Parsing the CoP time series into several timescales will lead to increased understanding of not only individual sensory systems but also the contribution of open-loop control to postural control. A dominant timescale was not observed in the CoP signal, consistent with the concept that several mechanisms are contributing to the CoP displacement. Very little energy was observed at the shortest timescales with gradually increasing energy at the moderate to long timescales, reflecting that closed-loop mechanisms have a relatively higher contribution to CoP displacement

compared to open-loop mechanisms. In this work, we have focused on 13 timescale ranges and found that the influence of vision, tapping tasks, or age can be captured in differences in energy content at these timescale ranges. For the present CoP data, our wavelet analysis does not focus on specific timescales that relate to specific neuromuscular loops. To isolate specific feedback loop timescales in the CoP data one may need to design experiments to specifically excite the specific feedback loop and the wavelet analysis, in principle, could be used to extract that effect in the CoP data.

Fig. 8 Average energy percentage change of vision effect with standard error for 13-level discrete wavelet transform decomposition of 70-s time series signals of the anterior-posterior CoP trajectory for all subjects using **a** Haar wavelet, **b** Discrete Meyer wavelet and **c** Biorthogonal 1.3 wavelet, with the corresponding wavelet shapes



While standing with the eyes closed, both young and older adults demonstrated increased energy for most of the timescales (Fig. 6a, c). Increased energy is consistent with the observation typically reported in the literature: sway increases with eyes closed (e.g. Paulus et al. 1984). However, the fine-grain nature of the wavelet analysis provides relevant, quantitative information about the energy levels at each timescale. For example, the decrease in energy content at the longer timescales is consistent with literature regarding the visual control of posture. Vision stabilizes sway primarily at frequencies below 0.1 Hz (e.g. Horak and Machpherson 1996; Oppenheim et al. 1999). The wavelet analysis strengthens the argument that vision stabilizes sway at low frequencies. However, it is important to note that the energy content at the longest timescales did not decrease 100%, i.e. mechanisms other than vision are still contributing to the low frequency component of the CoP time series.

As noted above, an increase in percent energy was observed at most of the timescales. Of these timescales, several ($j = 7-10$) are still within closed-loop timescales (critical point for open- versus closed-loop is about 1 s or 1 Hz, taken from Table 3 in Collins and DeLuca 1993). These timescales include frequency ranges that are sensitive to vestibular (0.1–0.5 Hz, $j = 8-10$) and somatosensory activity (0.5–1.0 Hz, $j = 7-8$) (Oppenheim et al. 1999). Assuming that these frequency bandwidths reflect the individual sensory systems, we can determine changes in contributions of the various sensory systems to the change in energy of the CoP data. Decreased energy in the 0.02–0.1 Hz timescales, coupled with increased energy at 0.1–1.0 Hz may reflect the nervous

system placing greater weight on the vestibular and somatosensory receptors when vision is unavailable, consistent with the idea of sensory weighting (e.g. Peterka 2002). In addition, subjects appear to rely more on open-loop control (greater than 1 Hz, or $j = 1-7$) when vision was removed. This open-loop control may manifest from the subjects adopting more of a stiffness strategy to compensate for the lack of visual feedback. Therefore, the young adults have adopted a strategy in the stand quietly without vision condition: decreased energy at long timescales—typically described as being controlled by vision—and increased energy at the moderate to short timescales—typically described as being controlled by vestibular, somatosensory, and open-loop mechanisms.

Older adults showed a similar pattern of changes when the eyes were closed (see Fig. 6e), but the magnitude was greater, with most changes double or greater for the older adults (Fig. 6e). Therefore, older adults adopted similar changes at each timescale, consistent with the idea that healthy older adults used similar strategies to stand without vision, only the magnitudes of the change were modified. Note that the largest changes occurred at the shortest time scales (Fig. 6e), indicating an increased reliance on open-loop mechanisms, such as increased stiffness. This is consistent with the findings of Collins and DeLuca (1995).

When performing concurrent tasks, performance on any or all tasks can be compromised if the combined capacity demands are greater than the amount of limited capacity attention available. This type of interference historically has been called capacity interference (Kahneman 1973). Cerebellar resources are required for both the timing task (Spencer et al. 2003) and the standing task (Woollacott and Velde 2008). Surprisingly, the change in energy while tapping showed a similar pattern to that observed for eyes closed, although the shape of the response is different and the response is different at the first two timescales (see Fig. 6a vs. b, c vs. d). That is, decreased energy was observed at the longer timescales with increased energy at the moderate and shorter timescales.

The decreased energy at the longer timescales may reflect that longer, larger amplitude sway oscillations may interfere with the ability to keep time to a 2-Hz beat. Therefore, energy was decreased to reduce “exploratory behavior” at low frequencies during this task. The increased reliance on the shorter timescales is consistent with the idea of weighted contributions of various mechanisms. As with vision, healthy older adults showed a similar change as young adults when tapping while standing with the eyes open (see Fig. 6b, d, e). As observed with the quiet standing with eyes closed condition, older healthy adults appear to use the same strategy as younger adults, with changes in the magnitude of energy change at several timescales.

The next point we wish to make is more speculative. We expected to find fairly diverse energy changes as a function of the postural manipulations due to the robust observation that postural performance is a function of context (see review in Horak 2004). However, we observed strikingly similar patterns at the multiple timescales; these patterns were observed independent of task and age. Energy decreased at the longest timescales when the eyes were closed or when subjects tapped at 2 Hz with the eyes open. Energy increased or stayed about the same at the moderate and short timescales for both manipulations. This leads to the postulate that, when examined at the level of time-scales, the nervous system adopts a fixed strategy when faced with a postural perturbation: increased energy at the shorter to moderate timescales and decreased at the longest timescales. The magnitude of the change may be specific to the perturbation but not the direction of change. Of course, our observations are limited to just two tasks, and many more observations are required to fully examine similarities and differences across multiple tasks and contexts. Overall, for both tasks and age groups, no single timescale demonstrated a relatively greater change than the remaining timescales. This is consistent with the idea that a single sensory system or control mechanism is not responsible for adapting to the postural manipulations, rather the various mechanisms all contribute, and their weighting is adjusted up or down.

When examining patient populations, such as Parkinson’s disease or multiple sclerosis, the wavelet analysis can discover differential changes at particular timescales, shedding light on the regulation and mechanisms of various components of the postural control system. Knowing the energy at several timescales would be especially useful for those disorders where the disrupted feedback loop is known, such as vestibular disorders or

‘visual vertigo’, where balance disruption is provoked by dynamic visual environments. These groups have been described as more “visually dependent” (Guerraz et al. 2001); the wavelet analysis would provide a fine grained analysis of changes in postural sway in this group, increasing our knowledge of postural control strategies in the face of disease.

Wavelet versus Fourier versus stabilogram diffusion analysis versus rambling and trembling

As mentioned earlier, the conventional analysis of CoP signals are performed using Fourier spectral methods. Fourier analysis breaks a time series signal into various sine wave frequency components; whereas, a wavelet analysis breaks a time series signal into scaled and translated mother wavelets. When comparing our wavelet analysis to the standard spectral analysis of other papers, the following key advantages of using the wavelet approach emerge when compared to the standard Fourier spectrum-based analysis:

1. It is easy to see that the wavelet analysis provides much more “sensitive” results for changes in postural conditions such as vision and age. A typical percentage change in MPF for a change in vision of healthy subjects is less than 10% (Laufer et al. 2006; Williams et al. 1997); whereas, the percentage change in our wavelet analysis for a change in vision of healthy subjects is up to 50%. Likewise, a typical percentage change in MPF for a change in age of healthy subject is less than 10% (Laufer et al. 2006; Williams et al. 1997), whereas the percentage change in our wavelet analysis for a change in age of healthy subjects is up to 100%.
2. The wavelet analysis provides “robust” results for changes in postural conditions such as vision and age. When examining the effects of vision, the results of typical MPF measurements for healthy subjects show relatively large error bars which overlap for the eyes open and eyes closed conditions (Laufer et al. 2006; Williams et al. 1997); likewise, when examining the effects of age, the results of typical MPF measurements for healthy subjects show relatively large error bars which overlap for the eyes open conditions for both young and elderly subjects and also for the eyes closed condition for both young and elderly subjects (Laufer et al. 2006; Williams et al. 1997). The findings of these experimental results are thus limited since no significant difference can be determined for these MPF measurements of different conditions. While our wavelet analysis does show error bars intersecting for some levels (mainly for small changes in levels), it is very clear that the error bars do not overlap for many cases through the different timescales of the signal, and as a result provide much more robust measures of changes in CoP dynamics with respect to age, vision, etc.
3. The wavelet approach provides a much deeper insight into which timescales are affected by changes in a neuromuscular feedback loop, while this information is not available with standard MPF approaches. This is because the wavelet approach examines the signal at multiple timescales and energy from the different timescales can be compared to show significant differences at different timescales. On the other hand, the MPF measurement lacks this timescale resolution as it is simply used to determine the mean frequency used in the signal. Upon examination of a DFT from the anterior–posterior CoP trajectory (see Fig. 7), it is clear that no key frequencies or timescales are dominant other than the very low frequency component. Some prior works have shown increased postural sway at specific moderate frequencies (Zatsiorsky and Duarte 1999). However, the DFT averages frequency components over the entire signal, transient occurrences cannot be identified. Therefore, a DFT is not able to discriminate the different timescale corrections that occur at the different time instants in the signal. Moreover, strictly speaking, Fourier analysis is applicable to stationary signals, and it is well documented that frequencies in postural sway change over time (e.g. Carroll and Freedman 1993; Schumann et al. 1995). However, wavelet transforms are particularly well-suited for intermittent, time-localized dynamics that occur in nonlinear systems with time delays.

These four main advantages of the wavelet approach over the Fourier approaches make wavelets an ideal tool for CoP time signals, and provide much more clear and significant results, which can be used to confidently distinguish differences in postural characteristics for different conditions.

Finally, we note that our emphasis in this work has been on quantifying energy content of the CoP signal at different timescales which involves the integration of WCs over the time series so that time-localized effects are not isolated but rather summed to the total energy content. Even so, as we have shown, the wavelet-based extraction of energy content at different timescales resolves the different energy content at different timescales much better than a Fourier transform-based energy analysis. This is because the mother and child wavelets better represent the CoP data locally compared to the smooth harmonic functions in Fourier analysis.

The stabilogram diffusion analysis proposed by Collins and Deluca (1993, 1994) has been used for the past 15 years to quantify the level of effective stochastic activity in open- and closed-loop control during quiet standing. The analysis determines the critical time interval to distinguish short- and long-term diffusion regions for each subject. The wavelet analysis provides information different from stabilogram diffusion analysis or the rambling–trembling analysis of Zatsiorsky and Duarte (2000). The wavelet analysis distinguishes between multiple time scales producing a finer grained output which is quantifiable and objective, and is complementary to the other analyses.

Effect of wavelet type

The energy analyses have been for a specific choice of wavelet function, the “Haar” wavelet. It is interesting to ascertain whether the results change if other wavelets are chosen to represent the data. Figure 8 shows the discrete wavelet transform energy percentage change in the vision effect for all subjects using the Haar, Discrete Meyer, and Biorthogonal 1.3 wavelet functions (Misiti et al. 1996). When taking a closer look at these three wavelets in the discrete wavelet transform analysis, it is seen that the Haar and Biorthogonal 1.3 wavelet functions both show similar trends in energy contents at different timescales, albeit with different percentage changes. The Discrete Meyer wavelet analysis also shows that postural corrections contain more energy at middle timescales when visions is removed, and the energy content is extremely sensitive to certain time-scales; however; the associated variance of change in energy content is quite large to draw any statistically relevant conclusions about the relative change at different timescales. In conclusion, the choice of wavelet for CoP analysis should be made while taking the following issues into consideration: (a) the variance of difference in energy content between postural manipulations needs to be small enough so that comparisons between timescales can be made with a high degree of confidence, and (b) if the focus is on examining changes at a specific timescale then there may be interest in choosing wavelets to provide great sensitivity to postural manipulations compared to others.

Conclusions

Wavelet transforms revealed changes in CoP dynamics that are not observable using more traditional analytical techniques. These changes were mapped to various feedback loops used in the maintenance of posture. With the eyes closed, energy was reduced at the longer timescales, consistent with the postulate that vision controls postural sway at low frequencies. Energy was increased at the short to moderate time scales, indicating a shift to vestibular and somatosensory feedback loops and open-loop control mechanisms. The secondary task resulted in a similar pattern of energy change: increased energy at short and moderate timescales coupled with decreased energy at the longest timescales.

Appendix 1: Calculating the energy content of the signal

The energy content at the level “ j ” can be expressed in terms of the detail WCs at that scale as,

$$E(j) = \sum_{k=0}^{K(j)} (T(j, k))^2 \quad (8)$$

Similarly, the total energy content of the signal can be found by summing the energy content of the approximated signal and the energy content over all J levels of the detail signals:

$$E_T = \sum_{k=0}^{K(J)} (S(J, k))^2 + \sum_{j=1}^J \sum_{k=0}^{K(j)} (T(j, k))^2, \quad (9)$$

where the energy at each discrete scale $j = 1, \dots, J$ and discrete location $k = 0, \dots, K(j)$ are summed. The energy content of the different scales can be expressed as a percentage of the total energy of the signal which is the sum

of the decomposed scale energies

$$E\%(j) = \left(\frac{E(j)}{E_T} \right) 100\%. \quad (10)$$

Appendix 2: Energy content percentage for vision effect

The percentage of energy content for the vision effect was examined by comparing the quiet standing with eyes open (SEO) and quiet standing with eyes closed (SEC) conditions for each trial of a subject as,

$$\Delta E_{EYE}\%(j) = \left(\frac{E_{SEC}\%(j) - E_{SEO}\%(j)}{E_{SEO}\%(j)} \right) 100\% \quad (11)$$

where $E_{SEO}\%(j)$ and $E_{SEC}\%(j)$ are the energy content percentages averaged over the three trials for the quiet standing with eyes open and quiet standing with eyes closed conditions, respectively. $\Delta E_{EYE}\%(j), j = 1, \dots, 3$ for one young individual (subject 14) are shown in Fig. 5c.

Appendix 3: Energy content percentage for tapping effect

The percentage of energy content for the tapping effect was examined by comparing the quiet standing with eyes open (SEO) and tapping with eyes open (TEO) conditions for each trial of a subject as

$$\Delta E_{TAP}\%(j) = \left(\frac{E_{TEO}\%(j) - E_{SEO}\%(j)}{E_{SEO}\%(j)} \right) 100\%. \quad (12)$$

where $E_{SEO}\%(j)$ and $E_{TEO}\%(j)$ are the energy content percentages averaged over the three trials for the quiet standing with eyes open and tapping with eyes open cases, respectively. The calculation was conducted for each of the young and older subjects.

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