Age-Related Changes in Centre of Pressure Trajectories Analysed with a Novel ‘Return to Central’ Analysis

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ABSTRACT. To evaluate age and fall-risk related changes in balance ability from measures of bipedal quiet stance, this study aims to investigate the characteristics of ‘return to central’ - Centre of Pressure (COP) trajectories. COP trajectories were extracted from 60-second COP recordings in bipedal stance. In anterior posterior direction, age was associated with a greater number of detected trajectories, increased velocity and more stringent control. No differences related to fall risk were established or to age or fall risk in mediolateral direction. The characteristics ‘return to central’ COP trajectories provided insight into the working of the postural control system and can be further developed for application if testing balance under challenging conditions is too risky.

Keywords: Postural control, ageing, falls, centre of pressure

Introduction

Elevated falls rates in older populations make a severe problem for our ageing society. Approximately one in three adults aged 65 or older experiences at least one fall each year, leading to injuries, decreases in quality of life and sometimes even death (Burns et al., 2016; Hartholt et al., 2012; King & Tinetti, 1995). Considering the world population is ageing (World Health Organization, 2015), this problem is only expected to get bigger in the coming years. On the positive side, an intense research effort is leading to an ever-increasing knowledge of fall prevention strategies (Sherrington et al., 2019) and risk factors (Ambrose et al., 2013). This understanding of falls in older adults has aided the development of some highly sensitive fall risk assessment tools (Park, 2018; Ruggieri et al., 2018). However, as these tools come with their individual strengths, they are not without limitations. That is, some of these measures are questionnaires or scales (e.g., Stapleton et al., 2009), in which verbal or written responses are made on items related to covariates of fall risk. Limitations to this approach are that the responses can be subjective, and this does not appeal to the actual mechanisms behind falling. In part, this can be overcome by implementing clinical tests, in which a health care professional observes the movement control of the participant in gait and balance (Horak et al., 2009; Tinetti et al., 1986). While these tests certainly appeal more to the mechanism of postural control, they still depend on the subjective assessment of the clinician. Finally, there are objective measures that are used to assess fall risk within a gait or balance task (e.g., Shumway-Cook et al., 2000). When these are combined with motion capture measures, one can gain an accurate insight in the working of the motor control system. One remaining limitation of these approaches is that to understand fall risk, posture is often challenged during these assessments, for instance by manipulating the standing surface, adding in a dual task or asking the participant to stand on one leg. These are important challenges as to understand fall risk, it is important to put the movement system in some level of risk. However, it might limit the ecological validity of the test (e.g., how often do older adults usually stand stationary on one leg?). Furthermore, this also excludes groups of participants from research studies that arguably form the most interesting cohort of study: people that have such deteriorations to their balance system that they can no longer complete these tasks, or older adults with cognitive declines (e.g., Alzheimer’s disease or dementia) who could have trouble understanding complex instructions. The current study introduces a novel method of analysis that can be used to magnify the balance control mechanisms that are present in even the simplest balance task, to create a new balance measure that can be applied to assess balance capabilities for people of all balance abilities.

In natural human stance, a person’s centre of pressure (COP) constantly fluctuates around its average position, a phenomenon known as postural sway. It has been long known that measures of postural sway can be informative on the functioning of the balance system, for instance showing that people with an elevated fall risk show elevated postural sway (Johansson et al., 2017). However, not all in postural sway might be bad, as movement variability has also shown to hold functional, explorative components (Davids et al., 2003). Postural sway provides an important means for the postural system for determining the characteristics of the limits of the stability (Riccio, 1993) and defining what postural movements are possible without risking a loss of balance (Riccio, 1993). Considering these different interpretations of postural sway, both relating to increased risks as well...
as explorative functioning, it becomes hard to determine what the aim would be of a single postural sway fluctuation, that is, a single COP trajectory from one point within the limits of stability to another. Such a COP trajectory could be the effect of a postural task (e.g., a person leans forward to grab something), it could be an effort to explore the dynamics of the postural system, it could represent random fluctuations that are common to the movement system (van Beers et al., 2002), it could be the result of a control effort, returning the COP to a stable region or, most likely, it is a combination of these factors all at once. It can be reasoned that from a general analysis of the COP position, it cannot be determined what the aim of the movement is; for instance, if the COP move forward away from its mean position, this could be explorative, it could be error or both. However, the current study reasons that to evaluate postural control mechanisms, one specific case can potentially be used that would represent mostly controlling movement activity. That is, although any single COP trajectory is likely influenced by an unknown mix of numerous factors, when the COP moves from the outskirts of the stability boundary back to the central area, it could be reasoned there would be a bigger influence of a control mechanism. These ‘return to central’ trajectories would still contain a random component and would still have an explorative function but, in general, this sort of movement would result for a relatively larger component from the control process (or, even when a single such trajectory appears through random fluctuations, when analysing numerous trajectories, on average the influence of the control process would be larger). As such, by focusing on just the ‘return to central’ trajectories, the current study hopes to establish an analysis that is more sensitive to changes in the control function of the postural system.

The current study aims to investigate the characteristics of ‘return to central’ COP trajectories during bipedal stance in terms of their frequency of occurrence, path length, velocity and control characteristics (operationalized using a tau-guidance analysis; Andel, Cole et al., 2019; Lee et al., 2009), to assess differences between participants that can be associated to age and falls risk. Within this investigation, it is important to differentiate between effects in the anterior-posterior (AP) and medio-lateral (ML) direction. With increasing instability, it is likely that the motor control system prioritises control towards the dimension in which there is a greater risk (Todorov & Jordan, 2002; Wachholz et al., 2019) of the COP moving outside the limits of stability (Todorov & Jordan, 2002; Wachholz et al., 2019). In regular bipedal stance, this is usually the AP direction, as the limits of stability in this direction are closer together compared to the ML direction. As instability increases with age and falls risk, we expect more stringent postural control, which we hypothesise to be associated with i, more return to central trajectories to be detected within a given time frame, ii, differences in the length and velocity of the trajectories, and iii, differences in control strategy (velocity profile) of the trajectories. These effects would be more prominent in the AP direction, which would be prioritised by the control system. In the ML, we expect smaller or no effects to occur. The current study builds on the premise that, while they would hold a random component as well, COP movements that constitute a return towards their mean position would best reflect the workings of a control system. Therefore, the characteristics of these trajectories might be informative of the workings of the balance system. To maximise applicability of this approach in population for whom a challenging stance might be impossible, it was decided to focus on these trajectories in one of the simplest balance tasks: bipedal quiet stance. The analysis has the potential to add to the understanding of age-related changes to the balance system and to fall risk, that has been built on research with conventional sway related variables.

**Materials and Methods**

**Dataset**

This study uses a previously recorded dataset, in which COP data is collected of 163 participants (Santos & Duarte, 2016a, 2016b), published open access on physionet.org (Goldberger et al., 2000). Ethical approval for collating this dataset was provided by the local ethics committee of the Federal University of ABC (#842529/2014) (Santos & Duarte, 2016a, 2016b). The dataset contains information from 116 females and 47 males, with an age between 18 and 86 years. Thirteen participants were not included in the current study due to the presence of neurological disorders that might have affected their balance abilities, leading to outliers in the analysis (Labyrinthitis, N = 12; Parkinson’s Disease, N = 1), leading to 150 participants being included in the current analysis.

The protocol of Santos and Duarte (2016a, 2016b) included measures of standing balance, lasting for 60 seconds each. Participants wore no shoes and their feet were positioned at an angle of 20 degrees lateral rotation with the heels 10 cm apart. They were instructed to stand as still as possible with their arms at the side of their body and to look at a target that was placed at eye height on the wall 3 metres in front of them. The assessment included 60 second measurements in four conditions, which were repeated three times per condition. The current study only includes an analysis of measures collected in the three trials in one single condition: eyes open on a stable surface.

Postural sway information was recorded using an AMTI force platform (40 × 60 cm, OPT400600-1000, AMTI, U.S.) and amplifier (Optima Signal Conditioner,
Data processing steps are described in Figure 1. The WFDB toolbox (Silva & Moody, 2014) was used to load the data into MATLAB (R2019b, The Mathworks Inc.), after which processing was completed using a custom algorithm. The algorithm aimed to detect when the COP position made a significant trajectory towards the central area (i.e., the area around the mean COP position). An important consideration here is that this analysis works under the assumption that the mean COP position reflects a stable region in posture space. However, in case of balance deficits with asymmetric weight bearing, this might not be the case and the mean COP position might be in an unstable position closer to the stability boundary. This should not be an issue in the current dataset where no such asymmetries were recorded, but is an important consideration if using this analysis on other datasets. A second consideration is that this central area should not be defined as a single ‘optimal’ point. Whilst it is likely that a mechanically most optimal/efficient postural configuration exists, it is has been reasoned that this is not a single point, but rather a moving point that migrates through the limits of stability (Zatsiorsky & Duarte, 2000). Furthermore, even if the postural system has a single (moving) target position, is does not specifically need to be in this exact spot to maintain stability. If the configuration is close to optimal, it will not cost much effort to maintain stability. There can thus be expected to be a region around the mechanical optimum configuration in which stability can be maintained without a significant increase in energetic costs. As such, any COP trajectory was considered that moves towards a loosely defined central area, as this would represent an increase in stability. Movement towards this central area was defined along the following parameters: firstly, trajectories were considered as starting and ending at 10% of their peak velocity (the 10% boundary was chosen rather than a complete stop in order to separate movements that might slow down to a near stop and continue with a second movement in the same direction; similar to Andel, Cole et al., 2019; Austad & Van Der Meer, 2007; Rasouli et al., 2016; Spencer & van der Meer, 2012). Second, trajectories were considered when starting more than 1.5 Standard Deviations (SD) away from the average COP position. Third, the minimal length of the trajectory was 1 SD. And fourth, the trajectory had to end before crossing the average COP position, or while overshooting it with a maximum of 1 SD.

Trajectories were extracted and pooled together from all three trials. Dependent variables were computed per trajectory and averaged values per participant were stored for the statistical analysis. Data processing steps are described in Figure 1. Processing was completed using the WFDB toolbox (Silva & Moody, 2014) to load the data and a custom algorithm written in MATLAB for further processing (R2019b, The Mathworks Inc.). The algorithm aimed to detect when the COP position made a significant trajectory from the outskirts of the limits of stability towards the central area (i.e., the area around the mean COP position). This was defined along the following parameters: firstly, trajectories were considered as starting and ending at 10% of their peak velocity (the 10% boundary was chosen in order to separate movements that might slow down to a near stop and continue with a second movement in the same direction; similar to Andel, Cole et al., 2019; Austad & Van Der Meer, 2007; Rasouli et al., 2016; Spencer & van der Meer, 2012). Second, trajectories were considered when starting more than 1.5 Standard Deviations (SD) away from the average COP position. Third, the minimal length of the trajectory was 1 SD. And fourth, the trajectory had to end before crossing the average COP position, or while overshooting it with a maximum of 1 SD. Trajectories were extracted and pooled together from all three trials. Dependent variables were computed per trajectory and averaged values per participant were stored for the statistical analysis.

Operationalisation and Dependent Variables

Three types of dependent variables were computed to summarise the spatiotemporal characteristics of the COP trajectories (see green section in Figure 1), all variables are collected for both the Anterior-Posterior (AP) as well as the Mediolateral (ML) direction. Firstly, we collect the average number of trajectories that were detected during the 60-second measures of standing balance.

For the second type of dependent variable, we focus on variables that have been shown to be related to fall risk. That is, Oliveira et al. (2018) showed that both a spatial measure (95% confidence ellipse area of COP) and spatiotemporal measure (average COP velocity) were significantly different between fallers and non-fallers in
FIGURE 1. Process of data analysis. Initial steps by Santos and Duarte (2016a) are depicted in the top three (yellow) boxes, the middle seven (blue) boxes represent processing steps and bottom five (green) boxes represent computation of dependent variables for the statistical analysis.
one-legged stance. In an attempt of translating this to an analysis on COP trajectories, the current study will focus on COP trajectory path length and COP trajectory average velocity. 

Finally, measures that are aimed to focus on the control characteristics of COP trajectories are included. To this end, an analysis into the tau-guidance characteristics was included (Lee, 1998, 2009). Such analysis has been previously used to study the movement of the centre of pressure in gait and balance (Andel, Cole et al., 2019; Austad & Van Der Meer, 2007; Rasouli et al., 2016; Spencer & van der Meer, 2012; Zhang et al., 2016) and other human movement such as head turns (Andel, McGuckian et al., 2019) and golf putting (Craig et al., 2000). The tau-guidance analysis assesses the velocity profile of a movement and computes the relation to a hypothetical reference movement that accelerates with a constant acceleration. The main outcome of this analysis is the ‘K-value’ or regression constant. If the K-value equals 1, it indicates a perfect coupling to this constantly accelerating movement and therefore a ‘hard’ closing of the movement with overshoot. Lower K-values indicate more deceleration at the end of a movement, where values under 0.5 indicate ‘soft contact’ with the endpoint (see bottom panel Figure 1 for a visual example using simulated data). K-values higher than 1 indicate a further acceleration past the defined endpoint. A second outcome of this analysis is an indication of how much of the movement holds an acceptable linear relationship with this smooth reference movement. This can be assessed, as the K-value is computed using a recursive linear regression. That is, if the relationship between the assessed movement and the reference movement yields an R-squared of less than 0.95, the furthest point in the assessed movement is dropped and the relationship is reassessed. This yields a variable that indicates the percentage of the movement that adheres to an acceptable linear relationship. We interpret this variable as how stringently a particular trajectory is controlled, that is, a low percentage would indicate only the final phase is controlled and a value close to 100 indicates nearly the complete trajectory is tightly controlled.

Statistical Analysis

The statistical analysis was completed using IBM SPSS Statistics (version 25). Multivariate Analyses of Variance (MANOVAs) were used to assess the influence of the grouping variables on the collection of dependent variables in the AP and ML direction separately. In case of working with larger samples, testing the assumption of equality of covariance matrices is likely going to yield a significant test result, without actually having a large difference between groups. In such case, it is recommended to work with equally sized groups, in which case the Pillai-Bartlett trace statistic is fairly robust to potential violations of the assumptions (Field, 2013). As such, to analyse the effect of age on the dependent variables, it was decided to create three equally sized age groups, with 50 participants each: the younger adult group (age 18 to 26), the middle group (age 27 to 65) and the older group (age 66 to 86). Considering the interdependence between age and fall risk (Figure 2), it was decided not to assess these factors in the same analysis. Rather, the effects of fall risk were tested in a separate MANOVA, in which only the oldest group was included. To separate the high-risk from the low-risk participants, the threshold Mini-BEST score of 19.5 was used that has been shown to differentiate between fallers and non-fallers in a previous study (Marques et al., 2016). To follow-up on any significant effects in the MANOVA analysis, separate ANOVAs were used to further investigate these effects. In case of significant age effects (with three levels), Bonferroni-corrected pairwise comparisons were used to assess which groups differed from each other significantly. Alpha for all tests was set at 0.05.

Results

The MANOVA investigating the influence of age categorisation on the collection of COP-trajectory related variables in the AP direction revealed a significant effect of age category on the outcome variables (Pillai-Bartlett trace = 0.238, F[10,288] = 3.888, p < 0.001, partial $\eta^2 = 0.119$). In ML direction no significant influences of age group were found (Pillai-Bartlett trace = 0.053, F[10,188] = 0.781, p = 0.647, partial $\eta^2 = 0.026$).

Follow-up ANOVA testing revealed the effect for age to be significant for the number of detected trajectories (F[2,147] = 18.106, p < 0.001, partial $\eta^2 = 0.198$), velocity (F[2,147] = 5.385, p = 0.006, partial $\eta^2 = 0.068$) and the percentage of the trajectories that adhered to the tau-guidance relationship (F[2,147] = 6.368, p = 0.002, partial $\eta^2 = 0.080$), but not for the path length (F[2,147] = 0.631, p = 0.533, partial $\eta^2 = 0.009$), and K-value (F[2,147] = 0.641, p = 0.528, partial $\eta^2 = 0.080$). Bonferroni-corrected pairwise comparisons revealed

![Figure 2. Distribution of participants over the grouping variables, group size is depicted in bar sizes as well as with the number above the bar.](image-url)
significant differences in the number of trajectories between the oldest group and the two other groups (old vs young: \( p < 0.001 \), old vs middle: \( p < 0.001 \)) but not between the younger two groups (\( p = 0.221 \)). This effect indicates that more trajectories were detected for people of older age (Figure 3A). For the trajectory velocity in AP direction, significant differences were found between the youngest and the oldest (\( p = 0.005 \)), but not between the other groups (young vs middle: \( p = 1.000 \), middle vs old: \( p = 0.076 \)), indicating higher velocity in the oldest compared to the youngest group. For the percentage coupling, significant differences were found between the youngest and oldest group (\( p = 0.001 \)), the middle group was not significantly different from either other group (young vs middle: \( p = 0.317 \), old vs middle: \( p = 0.164 \)). This effect indicates that people in the oldest age group had a significantly larger percentage coupling compared to the youngest group (Figure 3).

To investigate the effect of fall risk, a sub-group analysis was performed on the 50 oldest participants separated for high (\( N = 36 \)) and low (\( N = 14 \)) fall risk based on the Mini-BEST scores. In both AP as well as ML direction, MANOVA testing revealed the differences between groups to be insignificant (AP: Pillai-Bartlett trace = 0.097, \( F[5,44] = 0.947, p = 0.460 \), partial \( \eta^2 = 0.097 \); ML: Pillai-Bartlett trace = 0.139, \( F[5,44] = 1.423, p = 0.235 \), partial \( \eta^2 = 0.139 \)).

**Discussion**

The current study set out to investigate balance measures that can be implemented to study motor control mechanisms in a postural task without a challenging or non-representative manipulation to balance. The aim was to investigate the characteristics of ‘return to central’ COP trajectories during bipedal quiet stance. It was hypothesised that with increasing instability, these trajectories would be more numerous, show different lengths and velocities and be more controlled and that effects would mainly manifest in the anterior-posterior direction. The main result of this study partly supported the hypothesis. An age-related increase in the number of COP trajectories, their velocity and their control stringency in AP direction, supporting the hypothesis, but no differences were found in COP path length or Tau-guidance K-values. No significant differences were found to be associated with fall risk.

It should be considered whether these effects are related to age-related increases in instability, or potentially, they could be an indication of a control mechanism that works in a less stable system. That is, it could be that older adults, being more prone to postural instability, intervene with their postural control more frequently (leading to an increased number of detected trajectories) and more strongly (leading to an increased trajectory velocity and tau-coupling percentage). If the first option is true, and these effects are just indications of instability, then any further increase in these variables would be bad in terms of balance control. However, if the second option is true and this is an indication of a compensatory mechanism, then any deviation from this age-related increase might actually indicate risk. To differentiate between these two hypothesised mechanisms, a future study in which stability is directly manipulated would be feasible.

As expected, changes in trajectory characteristics manifested mainly in the AP direction. This finding fits well with the ‘Minimal Intervention Principle’ (MIP), a phenomenon associated with Optimal Feedback Control Theory (Todorov, 2004; Todorov & Jordan, 2002). According to this motor control theory, it is inefficient for the control system to stringently control all perturbations to the system. Therefore, the system learns to differentiate between perturbations that might endanger the outcome of a task (task-relevant variability) and variability that can exist without affecting the outcome. With age, we observe an increase in both AP and ML sway (Roman-Liu, 2018), but with the wider base of support in the ML direction, there is less relevance for stringent control in this direction. Indeed, the current study showed that with increasing age and fall risk, the control of the ML COP trajectories is largely unchanged, while the characteristics of AP trajectories showed many changes in outcome variables. A better understanding of the MIP in balance control could be of great relevance for balance training and fall prevention. Previous studies have observed that more conscious balance control (or movement investment) is associated with a higher fall risk (Wong et al., 2008). It could be hypothesised that when balance is controlled on a more conscious level, the individual attempts to control both task-relevant and irrelevant variability, as on a conscious level it is harder to differentiate between these two. It would be more efficient to trust the system to find the ‘minimal intervention’ and control just these fluctuations.

No effects were observed relating to fall risk as measured by the Mini-BEST assessment. It should be considered that the Mini-BEST test has been designed to identify balance deficits in individual patients, not specifically as a measure of fall risk (Franchignoni et al., 2010; Horak et al., 2009). As this measure has been shown to relate to fall risk in older adults (Marques et al., 2016), the current study used the established cut-off score to separate the oldest participants into a high and a low risk group. However, a further analysis on a wider age group might be feasible. To this end, further interpreting the descriptive results presented in Figure 3, some trends can be observed that the current study design was not equipped to fully explore but are worthwhile noting for consideration in future studies. Looking
FIGURE 3. Overview of means ± SD for analysed effects in age groups (separated by fall risk categorisation; darker bars for low fall risk). Note that the effects of age and fall risk were statistically assessed in separate MANOVA analyses to mitigate the effect of inter-reliance between independent variables. Significant age effects from the first analysis are represented by horizontal lines. Fall risk effects were only statistically assessed in the oldest age group, but no significant differences were found.
at the interaction between age and fall risk, it seems that differences that are present in the middle age group (Figure 3C–I) that disappear in the oldest age group. This might fit in well with the hypothesised compensation strategy and the MIP as introduced above. When these younger two groups experience any disturbances to their posture, they do not immediately threaten equilibrium and therefore do not yield a strong response every single time, however, for the less stable older group, any disturbance yields a similar response. This could explain why these observed effects of fall risk disappear in the oldest age group. Following this reasoning, it could be argued that a true indication of fall risk would be if a person would not increase these control parameters even in the face of instability. The here presented ‘return to central’ analysis could be a main component within this assessment, however, this concept will need to be developed further. This analysis provides insights into the motor response to instability, but should then be combined with measures that quantify the level of instability, so that a potential mismatch could be assessed.

Previous studies that assessed the tau-guidance characteristics of the COP in gait initiation have shown age (Spencer & van der Meer, 2012) and fall prevalence (Andel, Cole et al., 2019) to be associated with elevated $K$-values. The current study did not find any effects on $K$-values. One key difference in task that might have led to this finding is that in gait initiation the COP shifts away from a stable position all the way to one lateral side (the support foot). That is, the task itself means moving towards instability, which is done in a feedforward, ballistic fashion, while in the current study, we focussed on COP trajectories that lead towards a stable position. Thanks to the constant feedback loop that is required for these trajectories, it might be easier to mitigate age-related changes to the system.

The current study adds new understanding to the mechanisms of the control of posture during regular quiet stance. Even without a challenging task, the ‘return to central’ analysis developed here was sensitive enough to distinguish between people of different age groups and balance capabilities. This is an important finding to aid balance assessment in populations that might have trouble to maintain the challenging postures that are traditionally associated with objective evaluations of balance ability. However, it should be mentioned that this analysis might still not work for all populations. That is, the ‘return to central’ analysis works on the assumption that the mean COP position coincides with relatively stable region in posture space and thus that a ‘return to central’ always means an increase in stability. However, this might not be the case in all people, as in some disorders, postural asymmetries can be common. The generalisability of the current method is limited to those people where the mean COP position actually represents a relatively stable region in posture space.

It is a limitation of the current study that it cannot be determined whether this new analysis is more sensitive in determining fall risk compared to conventional measures of postural sway. It will be an important focus for future studies using a ‘return to central’ analysis to determine whether these methods provide a greater discriminatory power between fallers and non-fallers compared to traditional sway-related variables.

Another limitation with the current study needs to be considered. One of the reasons for completing the current study is to overcome the limitations that come with the existing clinical assessment of fall risk and balance disorders, and yet, we have trusted the Mini-BEST scores to provide an indication of fall risk. With the use of an open access database, the Mini-BEST scores were the best representation of fall risk available and they work well to serve an exploratory function in this study. We have found some effects related to this assessment of fall risk, which shows that there might be more effects to be explored in this field. It is a recommendation for future studies to further explore these findings using prospective falls diaries as a more valid indication of fall risk (Peel, 2000).

In conclusion, the current study aimed to investigate the characteristics of ‘Return to Central’ COP-trajectories to evaluate balance ability within a very simple balance task: bipedal standing with eyes open. The developed metrics were sensitive to reveal age-related changes: older age was associated with more trajectories that were controlled to a greater extend. We reason that the differences found between groups of different fall risk levels might be indicative of a compensatory strategy. Following this reasoning, it could be beneficial to train older adults to make longer COP movements, with a ‘soft contact’ strategy. The results of this study add to the already existing understanding of postural control mechanisms based on conventional sway variables and can be used to improve future fall risk assessments for people who might have trouble with more challenging postures.

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Disclosure statement

No potential conflict of interest was reported by the author(s).
Data availability statement

Data used in this study is available through the publicly available Human Balance Evaluation Database (Santos & Duarte, 2016a, 2016b; https://doi.org/10.13026/C2WW2W) which is made available under the ODC Attribution Licence (https://physionet.org/content/hbedb/view-licence/1.0.0/).

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