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# A Review of Center of Pressure (COP) Variables to Quantify Standing Balance in Elderly People: Algorithms and Open Access Code

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## Abstract

Postural control is often quantified by recording the trajectory of the center of pressure (COP) – also called stabilogram – during human quiet standing. This quantification has many important applications, such as the early detection of balance degradation to prevent falls, a crucial task whose relevance increases with the ageing of the population. Due to the complexity of the quantification process, the analyses of sway patterns have been performed empirically using a number of variables, such as ellipse confidence area or mean velocity. This study reviews and compares a wide range of state-of-the-art variables that are used to assess the risk of fall in elderly from a stabilogram. When appropriate, we discuss the hypothesis and mathematical assumptions that underlie these variables, and we propose a reproducible method to compute each of them. Additionally, we provide a statistical description of their behavior on two datasets recorded in two elderly populations and with different protocols, to hint at typical values of these variables. First, the balance of 133 elderly individuals, including 32 fallers, was measured on a relatively inexpensive, portable force platform (Wii Balance Board, Nintendo) with a 25-seconds open-eyes protocol. Secondly, the recordings of 76 elderly individuals, from an open access database commonly used to test static balance analyses, were used to compute the values of the variables on 60-seconds, eyes-open recordings with a research laboratory standard force platform.

## Keywords

Postural Control, Quiet Standing, Center of Pressure, Elderly.

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## 47 1 Introduction

48 The assessment of balance disorders is a common practice in geriatric care, as the problem of falls in the  
49 elderly is so serious in maintaining good health. As a major public health problem, falls are the leading cause  
50 of accidental death in the elderly, leading to serious psychomotor consequences and accelerating institutional-  
51 ization [WHO, 2008]. Health authorities recommend a standardised risk assessment for falls in the elderly that  
52 includes identification of risk factors and assessment of motor control. The latter is often carried out through  
53 functional clinical tests requiring the performance of one or more exercises while an operator assesses the  
54 feasibility of the task for the participant [Beauchet et al., 2011]. Limitations of functional tests relate to the  
55 ability to distinguish the systems disturbed in relation to imbalance (vestibular, visual, proprioceptive, motor,  
56 etc.), the provision of quantified and objective values, as well as a capacity to discriminate between fallers that  
57 is both more effective than a history of past falls and sufficiently sensitive to the evolution of balance capac-  
58 ities in the short and medium term [Mancini and Horak, 2010, da Costa et al., 2012, Balasubramanian, 2015],  
59 especially in extended care settings where the risk of fall is higher.

60 To address the lack of reliable clinical tests in the evaluation of balance and posture disorders, postur-  
61 ography aims at developing quantifiable analyses of postural control [Baloh et al., 1998b], mainly through  
62 the analysis of the trajectory of the center of pressure (COP). The COP trajectory is recorded using force  
63 platforms, which track the point of application of the ground reaction forces resultant under the feet. The  
64 resulting signal, called stabilogram, is frequently analysed using either its one dimensional variations in the  
65 mediolateral (ML) or anteroposterior (AP) direction, or its two-dimensional trajectory [Duarte and Zatsiorsky,  
66 2011, de Sá Ferreira and Baracat, 2014]. The COP signal is then described using a number of variables,  
67 which are used to evaluate the risk of fall. This approach has produced interesting results in the assess-  
68 ment of the risk of falling, in subjects with a balance degradation due to neurological impairment [Ojala  
69 et al., 1989, Vališ et al., 2012] or physiological aging [Colledge et al., 1994, Perrin et al., 1997, Baloh et al.,  
70 1998b, Camicioli et al., 1997]. In quiet standing, the COP is considered to reflect in part the motor mecha-  
71 nisms that ensure balance, precisely the maintenance of the projection of the center of mass (COM) inside the  
72 base-of-support [Hof et al., 2005]. There is a correlation between the displacement of the COP at the limits  
73 of stability and the incidence of falls, underlining the interest of exploring dynamic balance in determining  
74 the risk of falling [Johansson et al., 2019]. In addition, time-to-boundaries analysis has revealed significant  
75 spatio-temporal instabilities during voluntary excursion by leaning in all direction on force platform in elderly  
76 people compare to younger subjects [van Wegen et al., 2002]. Nevertheless, a simple test to quantify resting  
77 balance on a firm and stable surface is thought to already provide relevant information for the analysis of  
78 fall risk [Lord and Clark, 1996, Bauer et al., 2016b]. Thus, static posturography on a force platform could be  
79 a convenient tool for assessing the risk of falling, particularly for the oldest people for whom psychomotor  
80 disorders are known to exist and greatly limit the possibility of conducting functional tests that compromise  
81 their already precarious balance. The quantification of balance using a force platform is now commonly used  
82 [Pizzigalli et al., 2014].

83 Despite the relevance of exploring balance through quantified and explainable COP variables for the clini-  
84 cians, their computation suffers from significant drawbacks. First, studies may present different definitions of  
85 the same variable, or may not give a precise definition. For example, several variables rely on the calculation  
86 of peaks in particular signals obtained from the COP, however the method used for calculating these peaks is  
87 not explicitly defined, evoking notions of maximum values [Doyle et al., 2005] or high values between two  
88 "valleys" [Baratto et al., 2002] without any clear indication of a threshold in time or amplitude, and no clear  
89 algorithmic procedure. Moreover, the vocabulary used to introduce the variables sometimes varies from one  
90 study to another, making the identification of variables difficult, especially given that the equations used to cal-  
91 culate them are rarely provided. Secondly, the definitions of many of the COP variables rely on mathematical  
92 assumptions that are in general not clearly stated or verified (such as uniform resampling, see e.g. [Audiffren  
93 and Contal, 2016]). This lack of clarity can lead to contradictory conclusions between studies for the same  
94 variables [Delignières et al., 2011]. Finally, even when clear computation procedures have been presented in

95 the literature, some of them include several algorithmic steps which may not be convenient to code in the con-  
96 text of clinical practice [Collins and De Luca, 1993, Chiari et al., 2000], highlighting the need of developing  
97 open-access codes to compute the variables. The aforementioned drawbacks make it particularly delicate to  
98 compare the results of different studies and generalize their finding.

99 The number of available variables in the literature is also challenging. Indeed, in a previous systematic  
100 review [Quijoux et al., 2020], we identified more than fifty variables derived from the trajectory of the COP  
101 recorded in quiet stance to discriminate elderly fallers from non-fallers. A large number of these posturo-  
102 graphic variables can be calculated along the AP or ML directions and in the two-dimensional signal which  
103 further increases the quantity of variables that can be considered, leading to statistical problems related to data  
104 dimensionality. Moreover, since the semiological understanding of posture disorders is relatively limited, no  
105 consensus has been reached regarding the grouping of these variables under large physiological classes that  
106 could alleviate this problem – as may have been the case with gait [Mansour et al., 2017, Vienne et al., 2017].

107 The objective of this review is to propose a compendium of definitions of the COP variables that  
108 are the most frequently found in the literature to compare elderly fallers from elderly non-fallers, based  
109 on a systematic review [Quijoux et al., 2020]. The lack of standardised methods and analysis procedures  
110 has been proposed to explain discrepancies of results with similar analysis [Kirchner et al., 2012]. Ac-  
111 cordingly, we aim to facilitate the comparison between studies through a review of the scientific lit-  
112 erature as well as the computation and the presentation of the values for the selected variables. The  
113 method of variable selection is presented below. In accordance with our selection process (see Sec-  
114 tion 2.1 and 2.2), we did not include in this review several postural control models and variables  
115 [Hernandez et al., 2015, Hur et al., 2012, Sakanaka et al., 2016, Reed et al., 2020], that were not used in the  
116 clinical examination of elderly people at risk of falling. Additionally, and to help the identification and com-  
117 prehension of the variables, we also propose a new classification that reflects the aspects of the COP trajectories  
118 they are designed to capture: positional, dynamic, frequency and stochastic variables. We hope that by provid-  
119 ing this compendium, future works may compare and aggregate more easily their results. Furthermore, and to  
120 help the use of these variables, we propose a descriptive analysis of their behaviour on two databases of COP  
121 trajectories recorded in elderly people. We provide the average values and standard deviation of each variable  
122 on both datasets, in order to provide a baseline for typical values or order of magnitudes that can be expected  
123 for these variables in an elderly population. Note that these datasets present a large variability of medical  
124 profiles, and have been collected with different protocols and equipments, thus hinting at the general scope of  
125 the indexed variables. The contribution of these two datasets is to present values from the same calculation  
126 methods, but for different experimental conditions, which we hope will provide a means of comparison for  
127 future users of these algorithms.

## 128 2 Method

### 129 2.1 Literature review

130 A systematic review of the literature was originally conducted to identify articles that addressed the dis-  
131 crimination of older people at risk of falling. Randomized control trials (RCT), non-randomized control trials,  
132 and observational studies were all eligible for inclusion. Articles analyzing the balance through COP record-  
133 ings during quiet standing with both feet on the ground and evaluating the risk of falling by the number of falls  
134 during a period of time (retrospectively or prospectively) were selected. Five databases (PubMed, Cochrane  
135 CENTRAL, EMBASE, and ScienceDirect) were used as sources for published articles. The search was per-  
136 formed for all articles published (without date restriction) until July 1, 2019. In addition, a search of "grey"  
137 literature [Conn et al., 2003] was performed which included items like reports, theses and studies that were  
138 found online using Google Scholar, ClinicalTrials.gov sources, Google, theses.fr, HAL, ResearchGates and  
139 ethos.bl.uk. All reference lists from included studies were reviewed for additional relevant studies. The papers  
140 had to be written in a language understood by the authors (i.e. English, French, Italian, Spanish or German).  
141 The choice was made to include a wide range of study types and not to limit the study to RCT in order to have  
142 a broad view of the COP analysis methods used to differentiate between fallers and non fallers of 60 years and  
143 older.

144 The keywords were selected following the P.I.C.O framework to produce research equations such as  
145 "[OLDER ADULTS] + [QUIET STANDING] + FALL\* + DIFFERENC\*" (the exhaustive list is published  
146 in the protocol). The following MeSH terms were also used: "Accidental Falls/prevention & control", "Ac-

147 cidental Falls/statistics & numerical data\*”, ”Aged”, ”Postural Balance/physiology\*”, ”Posture/physiology\*”,  
148 ”Predictive Value of Tests” and ”Regression Analysis”. The general design was in accordance with PRISMA  
149 and MOOSE guidelines. We refer the reader to PROSPERO database (CRD42018098671) and the published  
150 protocol [Quijoux et al., 2019] for more details.

151 Studies, and the variables extracted from them, were included if the research involved a comparison of older  
152 people with and without a history of falls (retrospective studies) or longitudinal follow-ups of these elderly  
153 people with regular measurement of the number of falls (prospective studies). Analyses of COP trajectories  
154 should be clearly stated, as well as the protocol for recording balance, excluding recordings of dynamic balance  
155 with instructions such as bending forward, repositioning after destabilisation or standing on one foot. It is  
156 of practical interest for balance analysis to distinguish between older people on the basis of their number  
157 of falls. Many studies have shown differences between healthy and young subjects compared to the elderly  
158 [Condron et al., 2002, Pizzigalli et al., 2014, King et al., 2016], but from a clinical point of view it seems more  
159 relevant to focus on the studies comparing individuals of the same age group.

## 160 2.2 Selection of COP variables

161 The variables presented in this work were selected as follows. Based on [Quijoux et al., 2020] – a recent  
162 systematic review of the COP characteristics that were used to identify fall risk in elderly – and the afore-  
163 mentioned criterion, we identified 27 articles presenting results using measurements derived from the COP  
164 trajectory. Among the variables introduced in those articles, we selected all those that satisfied the following  
165 inclusion criteria:

- 166 • Must be used in at least two different articles
- 167 • Must be tested to distinguish older people at risk of falling from a control group, even if the variable is  
168 not discriminating
- 169 • Must be sufficiently described, with enough details, to be reproducible. This includes formal mathemat-  
170 ical definition such as equations, or explanations of computation methods.

171 It should be noted that for some variables included in this study, the description in previous works was  
172 only partial. In this case, additional hypotheses were made to permit the computation of the feature, and these  
173 assumptions are clearly stated in the paragraphs of this study dedicated to the sway variables concerned.

## 174 2.3 Corpus of the selected variables

175 Each variable is presented with references to its computation in previous studies and the algorithm that  
176 enables its calculation. The variables are grouped in four families to ease the reading of this study, according  
177 to their reliance on different aspects of the COP trajectories:

- 178 • Positional variables  
179 Variables that describe characteristics of the dispersion of the trajectory or position of the feet, and do  
180 not require the knowledge of the dynamics of the signal.
- 181 • Dynamic variables  
182 Variables based on the dynamic of the COP, requiring the knowledge of its local displacements.
- 183 • Frequency variables  
184 Variables used to describe the Power Spectral Density of the COP trajectory.
- 185 • Stochastic variables  
186 Variables derived from the models in which the COP is represented as a stochastic process.

187 A more detailed description of each group is provided at the beginning of its respective part, in Section 3. It is  
188 important to note that these categories are not necessarily orthogonal, in the sense that features inside different  
189 groups could possibly be correlated. The classification inside distinct groups is nevertheless useful as these  
190 features rely on different models or mathematical concepts and therefore lead to interpretations of different  
191 nature. For instance, some stochastic features which are linked to diffusion phenomena could be positively  
192 correlated to positional features that also measure dispersion aspects of the signal, however in the first case the

193 computation of the feature relies on a model of stochastic diffusion whereas in the second case the dynamic of  
194 the trajectory is not taken into account, leading to different interpretations.

## 195 2.4 Data collection

196 The clinical Research Ethics Committee approved the clinical study, registered at ANSM (ID RCB 2014-  
197 A00222-45).

198 **Participants** Elderly people with or without balance impairments were recruited during routine consulta-  
199 tions in neurology departments (Val-de-Grace Hospital) and physical medicine and rehabilitation departments  
200 (Fernand Widal Hospital, Paris, France). 133 individuals were included, 32 of them with recent history of falls  
201 (fallers: at least 1 fall in the previous 6 months). The participants included in this study were aged at least 60  
202 years old.

203 **Experimental procedure** During these consultations, and before the experiment, patients were asked about  
204 their history of falls in the last six months. Measurement of the COP displacement characteristics of the in-  
205 dividuals were then performed using a Wii Balance Board (WBB) (Nintendo, Tokyo, Japan), an alternative  
206 to laboratory grade force platform that have received increased attention in the recent years for quantifying  
207 postural control [Park and Lee, 2014, Severini et al., 2017]. The use of the WBB is justified by its advan-  
208 tages in terms of convenience compared to laboratory force platforms. Its within-device and between-device  
209 reliability have been considered good and suitable for clinical settings [Clark et al., 2010], especially when pre-  
210 processing methods are applied to improve accuracy [Leach et al., 2014, Audiffren and Contal, 2016]. During  
211 the static balance recording, patients were invited to stand on the platform. Data was collected by a custom  
212 software on a Samsung tablet (Android operating system version 2.0, Samsung, Seoul, Korea), using Bluetooth  
213 L2CAP protocol. The balance test was performed twice with different conditions. First, the individuals stood  
214 in quiet stance, eyes open, looking straight ahead, arms at their sides and feet comfortably positioned within  
215 the space provided on the WBB. After 10 seconds in this position, the trajectory of the COP was recorded  
216 for 25 seconds, a duration that has been shown to be sufficient to quantify postural control with variables  
217 [Bargiotas et al., 2018]. Then the individuals were asked to close their eyes. After a further 10 seconds, the  
218 closed-eye recording was started for 25 seconds. Between the two phases, there was no rest period, except in  
219 case of vertigo expressed by the subject. For the calculation of the variables, only the open eyes record is kept  
220 (a single repetition).

221 **Data Preprocessing** Data preprocessing and analysis software were written using Python (v3.7, Python  
222 Software Foundation, OR, USA). The signals collected from the force platform were resampled at 25 Hz  
223 using SWARII [Audiffren and Contal, 2016], as the WBB is known to produce data at non uniform frequency.  
224 Then, resulting force platform data were processed with a fourth-order, zero-lag, low-pass Butterworth filter  
225 with a 10 Hz cutoff frequency, in accordance to [Hernandez et al., 2015].

226 Finally, due to the variability of foot positioning on the force platform, we chose to center the COP trajec-  
227 tories with respect to their arithmetic mean in our definitions and analysis, in line with most of previous studies  
228 [Prieto et al., 1996, Qiu and Xiong, 2015].

229 **Public data set of human balance** Due to the lack of consensus on the methods of recording and analysing  
230 posturographic signals, a public data set was made available to allow comparison and testing of analysis  
231 methods [Santos and Duarte, 2016a]. The data set was constructed by a single experimenter at the Laboratory  
232 of Biomechanics and Motor Control at the Federal University of ABC, Brazil. Only the COP displacements of  
233 participants aged 60 and over, from this public data set, were used to calculate the variables presented above.  
234 The data in this set are resting balance recordings on a force platform (OPT400600-1000; AMTI, Watertown,  
235 MA, USA), for 60s, at a sampling rate of 100 Hz. We use the averaged value on the three recordings made  
236 for each participant. To be consistent with our recording protocol, only data from the firm-surface, open-eye  
237 recordings were used. Participants were asked to remain as steady as possible with their arms at their sides and  
238 to look at a target in front of them. The position of the feet was standardised as follows "with an angle of 20  
239 degrees between them and their heels were kept 10 cm apart". The forceplate data were preprocessed through  
240 a 10 Hz 4th order zero lag low-pass Butterworth filter. More details are available in the original publication  
241 [Santos and Duarte, 2016b].

242 **Sample Characteristics** 133 people recorded with the Wii Balance Board were included in this study. The  
 243 demographics characteristics of participants are shown in Table 1. The mean age in this sample is high but  
 244 corresponds to the populations presented by other authors [Aufauvre et al., 2005, Bauer et al., 2016a, Maki  
 245 et al., 1994, Muir et al., 2013, Ramdani et al., 2013, Bigelow and Berme, 2011, Borg and Laxåback, 2010,  
 246 Hewson et al., 2010]. The incidence of the number of falls among people over 80 years of age was measured  
 247 at nearly 6 falls per year (5,930 for women and 5,467 for men in 2009) [Korhonen et al., 2012], which is  
 248 consistent with the number of falls over the last 6 months in this study. In addition, the elderly participants  
 249 characteristics of the public data base are presented in Table 1. We can note that the proportion of fallers  
 250 in the two groups is close to 25%, although the average ages, the retrospective period during which falls are  
 251 investigated and the average number of falls are different.

	WBB dataset	Public dataset
Total	133	76
Men	72	16
Women	61	60
Age	78.7 ( $\pm$ 6.7)	71.3 ( $\pm$ 6.5)
BMI	24.4 ( $\pm$ 4.1)	25.5 ( $\pm$ 2.9)
Fallers	32 (6 last months)	19 (12 last months)
Number of falls (for fallers)	2.3 ( $\pm$ 2.4)	3.8 ( $\pm$ 11.7)

Table 1: Characteristics of study participants

## 252 2.5 Descriptive analysis

253 **Variables distributions** In order to provide indicative values for the variables presented, we report the means  
 254 and standard deviations for both populations, for each of the COP variables during eyes-open recordings.  
 255 Fallers and non-fallers are aggregated for each database since the objective is not to discriminate between sub-  
 256 populations of the samples according to their fall risk or pathologies. Note that we chose not to include in our  
 257 analysis two aforementioned variables, MEAN VALUE and VFY, in line with previous studies concerns about  
 258 the considerable measurement errors that these features are prone to [Duarte and Freitas, 2010] – a problem  
 259 that is compounded here as our study was multi-centric, which inherently increased the probability of small  
 260 variations between the participant feet position.

## 261 2.6 Open-access code

262 A code enabling the calculation of all the COP variables that are presented is available at  
 263 [https://github.com/Jythen/code\\_descriptors\\_postural\\_control](https://github.com/Jythen/code_descriptors_postural_control).

## 264 3 Results

### 265 3.1 General notations

In the following, we assume that the recorded COP trajectory contains  $N$  data points, sampled at constant frequency  $F_s$ .  $T = N/F_s$  denotes the total duration of the signal in seconds. For each  $1 \leq n \leq N$ ,  $ML_n$  (respectively  $AP_n$ ) denotes the coordinate of the COP position at time  $n/F_s$  on the ML axis, from left to right, (respectively the AP axis, from backward to forward). Then for each  $1 \leq n \leq N$ ,

$$X_n = ML_n - \frac{1}{N} \sum_{i=1}^N ML_i$$

and

$$Y_n = AP_n - \frac{1}{N} \sum_{i=1}^N AP_i$$

represent the coordinates of the centered trajectories on the ML axis and AP axis, respectively. We also introduce the Radius signal  $(R_n)_{1 \leq n \leq N}$  as the euclidean distance of the centered COP to the origin: for each

$$1 \leq n \leq N,$$

$$R_n = \sqrt{X_n^2 + Y_n^2}.$$

Finally, we define the covariance between the AP and ML variations of the COP as

$$\text{COV} = \frac{1}{N} \sum_{n=1}^N X_n Y_n$$

Symbol	Name	Formula	Units	Section
T	Total duration of the signal	-	s	
N	Number of points of the signal	-	-	
$F_s$	Sampling Frequency	$N/T$	Hz	
$ML_n$	Medio-Lateral (ML) Coordinates	-	cm	
$AP_n$	Antero-Posterior (AP) Coordinates	-	cm	
$X_n$	Centered ML Coordinates	$ML_n - \frac{1}{N} \sum_{i=1}^N ML_i$	cm	
$Y_n$	Centered AP Coordinates	$AP_n - \frac{1}{N} \sum_{i=1}^N AP_i$	cm	3.1
$R_n$	Radius	$\sqrt{X_n^2 + Y_n^2}$	cm	
COV	Covariance AP ML	$\frac{1}{N} \sum_n X_n Y_n$	cm <sup>2</sup>	
$SD_n$	Sway Density	see Def. 1	s	
$z_\ell$	Zero Crossing	see Def. 3	-	
$p_\ell$	Peaks	see Def. 4 and 2	-	3.3
$V_n^x$	ML Velocity	see Computing velocity and Notation	cm.s <sup>-1</sup>	
$V_n^y$	AP Velocity	see Computing velocity and Notation	cm.s <sup>-1</sup>	
$V_n$	Velocity norm	$\sqrt{(V_n^x)^2 + (V_n^y)^2}$	cm.s <sup>-1</sup>	
$\Gamma_k^S$	PSD of $S$ for frequency $kF_s/N$	-	cm <sup>2</sup> .Hz <sup>-1</sup>	3.4
$M_\ell^S$	$\ell$ -th Spectral Moment of $S$	$\sum_k f_k^\ell \Gamma_k^S$	cm <sup>2</sup> .Hz <sup><math>\ell-1</math></sup>	
$\text{MSD}^S(\Delta t)$	Mean Square Displacement of $S$	$\frac{\sum_n (S_{n+F_s \Delta t} - S_n)^2}{N - F_s \Delta t}$	cm <sup>2</sup>	3.5

Table 2: General notations and signal transformations used in the definition of the features. For each quantity, we report the symbol used in this manuscript, the name of the symbol, the formula, the units, as well as the section where the feature is defined. Note that  $S$  is a placeholder symbol that can be replaced by both  $X$  (ML coordinates) and  $Y$  (AP coordinates).

## 3.2 Positional variables

Variables are classified in this category if they depend on the COP positions and do not require the knowledge of its local displacements. Therefore these descriptors can capture characteristics of the dispersion of the trajectory or a favoured position for the point of support of the feet, and do not embed dynamic aspects of the signal, as they ignore the temporal nature of the data.

**Mean Value** The mean position, computed as the arithmetic average of the COP trajectory before centering, has been considered by [Aufauvre et al., 2005, Stel et al., 2003, Brauer et al., 2000, Maki et al., 1994], for the ML and AP coordinates. Importantly, previous works have disagreed with the use of this variable [Duarte and Freitas, 2010], given the variability in the placement of the feet on the force platform.

$$\text{MEAN ML} \quad \frac{1}{N} \sum_{n=1}^N ML_n$$

$$\text{MEAN AP} \quad \frac{1}{N} \sum_{n=1}^N AP_n$$



Feature	Full Name	Formula	Units
MEAN ML	Mean ML Coordinate	$\frac{1}{N} \sum_n ML_n$	cm
MEAN DIST. ML	Mean Distance ML	$\frac{1}{N} \sum_n  X_n $	cm
MEAN DIST.	Mean Distance	$\frac{1}{N} \sum_n  R_n $	cm
MAX ML	Maximal Distance ML	$\max_n  X_n $	cm
MAX RADIUS	Maximal Distance	$\max_n  R_n $	cm
RMS ML	Root Mean Square ML	$\sqrt{\frac{1}{N} \sum_n X_n^2}$	cm
RMS RADIUS	Root Mean Square Radius	$\sqrt{\frac{1}{N} \sum_n R_n^2}$	cm
RANGE ML	Amplitude ML	$\max_{n,m}  X_n - X_m $	cm
RANGE ML-AP	Amplitude ML-AP	$\max_{1 \leq n \leq m \leq N} \sqrt{(X_n - X_m)^2 + (Y_n - Y_m)^2}$	cm
RANGE RATIO	Ratio of amplitudes	$\frac{\text{RANGE ML}}{\text{RANGE AP}}$	-
PLANAR DEV.	Planar Deviation	$\sqrt{\text{RMS ML}^2 + \text{RMS AP}^2}$	cm
COEF. SWAY DIR.	Coefficient of Sway Direction	$\frac{\text{COV}}{\text{RMS ML} \times \text{RMS AP}}$	-
95 % CONF. AREA	95% Confidence Ellipse Area	see Def.	cm <sup>2</sup>
PRINCIPAL SWAY DIR.	Principal Sway Direction	$\arccos \left( \frac{ v_2 }{\sqrt{v_1^2 + v_2^2}} \right) \times \frac{180}{\pi}$	°

Table 3: Summary of the definition of the positional features. All the listed ML features can also be computed for the AP axis. For units, cm stands for centimeter, ° for degree (angle), and – for unitless.

277 **Mean Distance** This feature represents the mean distance of the COP from the center of the trajectory [Pri-  
278 eto et al., 1996, Maranesi et al., 2016, Qiu and Xiong, 2015], which we estimate as the empirical average  
279 of the signal. Therefore, we define the mean distance using the centered signal, see the paragraph General  
280 notations. According to the authors, this descriptor could be related to the stability of the postural system.  
281 Age differences were found with higher values in the ML direction, especially in older women compared to  
282 younger participants or men [Kim et al., 2010]. This variable also showed sensitivity to the size of the support  
283 base as it was found to decrease monotonically, especially in the ML direction, as the distance between the  
284 feet increased [Kim et al., 2014a]. Regarding falls, [Maranesi et al., 2016] have not either found significant  
285 differences for this feature between elderly fallers and non-fallers in both ML and AP directions.

286 MEAN DIST. ML  $\frac{1}{N} \sum_{n=1}^N |X_n|$

287 MEAN DIST. AP  $\frac{1}{N} \sum_{n=1}^N |Y_n|$

288 MEAN DIST.  $\frac{1}{N} \sum_{n=1}^N R_n$

289 **Maximal Distance** This feature has been defined as the maximal distance of the COP from the centroid  
290 [Muir et al., 2013], which we interpret as the center of the trajectory. Similarly to the Mean Distance, we  
291 define this feature as the maximum of the centered signal. This descriptor has been shown to be significantly  
292 greater in elderly fallers than in non fallers [Muir et al., 2013].

293 MAX ML  $\max_{1 \leq n \leq N} |X_n|$

294 MAX AP  $\max_{1 \leq n \leq N} |Y_n|$

295 MAX RADIUS  $\max_{1 \leq n \leq N} R_n$

296 **Root-Mean-Square (RMS)** The RMS is calculated on the centered trajectory. In the ML and AP axis it  
 297 corresponds to the standard deviation of the trajectory and on the two dimensional signal it is the square  
 298 root of the arithmetic mean of the squared radius [Prieto et al., 1996]. Previous works have found changes  
 299 associated with ageing in this feature direction [Maki et al., 1994], particularly in the ML direction [Piirtola  
 300 and Era, 2006, Swanenburg et al., 2010]. [Bargiotas et al., 2018] also used successfully the RMS on the ML  
 301 axis for their classification model between elderly fallers and elderly non-fallers. However, [Laughton et al.,  
 302 2003] found significant differences between elderly non-fallers and young participants for the AP standard  
 303 deviation but not in the ML direction.

$$304 \text{ RMS ML} \quad \sqrt{\frac{1}{N} \sum_{n=1}^N X_n^2}$$

$$305 \text{ RMS AP} \quad \sqrt{\frac{1}{N} \sum_{n=1}^N Y_n^2}$$

$$306 \text{ RMS RADIUS} \quad \sqrt{\frac{1}{N} \sum_{n=1}^N R_n^2}$$

307 **Range (Amplitude)** The range, also called amplitude, of the COP path, has been widely used in the literature  
 308 [Aufauvre et al., 2005, Bauer et al., 2010, 2016a, Maranesi et al., 2016, Ramdani et al., 2013, Howcroft et al.,  
 309 2015, 2017, Laughton et al., 2003]. In [Prieto et al., 1996] the authors define the range as the maximal distance  
 310 over two points of the stabilogram. Along one particular axis, this is mathematically equivalent to the distance  
 311 between the maximum and the minimum position of the signal. Previous works have shown contradictory  
 312 results regarding the predictive power of this variable for the assessment of fall risks, but it has been shown  
 313 that the RANGE in the ML direction differs between fallers and non-fallers based on a meta-analysis of data  
 314 from elderly participants with a history of falls, in a previous systematic review [Quijoux et al., 2020].

$$315 \text{ RANGE ML} \quad \max_{1 \leq n \leq m \leq N} |X_n - X_m|$$

$$316 \text{ RANGE AP} \quad \max_{1 \leq n \leq m \leq N} |Y_n - Y_m|$$

$$317 \text{ RANGE AP-ML} \quad \max_{1 \leq n \leq m \leq N} \sqrt{(X_n - X_m)^2 + (Y_n - Y_m)^2}$$

318 **Ratio of Amplitudes (Quotient of Both Directions)** The ratio of the COP dynamics in ML and AP direction  
 319 has been frequently studied in regards to the balance strategy involved to maintain erect posture in elderly  
 320 people. [Błaszczuk et al., 2014] computed the directional index as the ratio of the AP or ML path lengths  
 321 divided by the total COP length. In [Bauer et al., 2016a], the quotient of both directions is defined as the ratio  
 322 of mediolateral amplitude over the anteroposterior amplitude, and this measure is shown to be significantly  
 323 different between fallers and non-fallers during eyes closed recordings [Bauer et al., 2010].

$$324 \text{ RANGE RATIO} \quad \frac{\text{RANGE-ML}}{\text{RANGE-AP}}$$

325 **Planar Deviation** The planar deviation was defined by [Raymakers et al., 2005] as the square root of the sum  
 326 of the variances of displacements in ML and AP directions. While it has been argued that this variable may be  
 327 less discriminant than the range or the mean velocity [Raymakers et al., 2005] and has shown a small relative  
 328 reliability, with an intraclass correlation coefficient (ICC) of 0.5, in eyes open condition, and a poor absolute  
 329 reliability [Qiu and Xiong, 2015], the planar deviation has been used in multiple previous works to quantify  
 330 human stability [Xiong and Karim, 2013, Ilett et al., 2016].

$$331 \text{ PLANAR DEV.} \quad \sqrt{\text{RMS ML}^2 + \text{RMS AP}^2}$$

332 **Coefficient of Sway Direction** [Bauer et al., 2016a] has defined the coefficient of sway direction as the ratio  
 333 of the covariance between AP and ML directions over the marginal standard deviations, i.e. as the coefficient of  
 334 correlation between the ML and AP trajectories. This descriptor has been shown to be significantly associated  
 335 with falls [Bauer et al., 2016a] in community dwelling older adults.

$$336 \text{ COEF. SWAY DIR.} \quad \frac{\text{COV}}{\text{RMS ML} \times \text{RMS AP}}$$

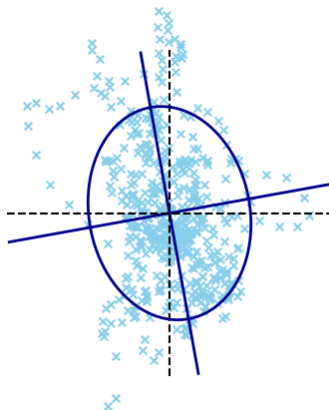


Figure 1: Illustration of the calculation of the 95% confidence ellipse. The feature is equal to the area of the ellipse.

337 **95% Confidence Ellipse Area (Sway Area)** The confidence ellipse area (or sway area) is not always com-  
 338 puted with the same definition and method in stabilometry studies [Schubert and Kirchner, 2014] Two main  
 339 definitions area used. One of the definitions used is related to the mathematical definition of an confidence  
 340 ellipse area, which is the area of the ellipse that contains the true mean of the signal with a high probability,  
 341 and the other is related to the mathematical definition of a prediction ellipse area, which is the area of the el-  
 342 lipse that would contain a future observation with high probability [Schubert and Kirchner, 2014]. One major  
 343 drawback with the first definition and that it depends strongly on sample size. In this review, we propose to  
 344 use the prediction ellipse area definition, which show marginal variations with change in sample size [Schu-  
 345 bert and Kirchner, 2014]. An increase of this feature value among elderly people has been associated with a  
 346 significantly higher risk of fall [Merlo et al., 2012]. The feature is derived from using the central limit theorem  
 347 [Schubert and Kirchner, 2014, Prieto et al., 1996, Duarte and Freitas, 2010], which requires the assumption  
 348 that the serie samples are independent and identically distributed. Let  $F_{0.95,2,n-2}$  denote the 0.95-quantile of  
 349 the Fisher distribution with 2 and  $n - 2$  degrees of freedom. Note that the unbiased versions of the covariance  
 350 matrix could also be used [Schubert and Kirchner, 2014]. The feature can be approximated by the following  
 351 formula

$$352 \text{ 95 \% CONF. AREA} \quad 2\pi \times \frac{(N-1)(N+1)}{(N-2)N} \times F_{0.95,2,N-2} \times \sqrt{\text{RMS ML}^2 \times \text{RMS AP}^2 - \text{COV}^2}$$

353 An illustration of the calculation of this feature is shown in Figure 1.

354 **Principal Sway Direction** [Oliveira et al., 1996] introduced the principal sway direction as a tool to represent  
 355 the relative contribution of the ML and AP components to the oscillations of the COP. The computation of the  
 356 sway direction is based on a Principal Component Analysis (PCA) which derives the direction of maximum  
 357 dispersion of the COP trajectory. The principal direction is defined as the angle, between  $0^\circ$  and  $90^\circ$ , between  
 358 the AP axis and the direction of the main eigenvector produced by the PCA. [Rocchi et al., 2004] has claimed  
 359 that this variable provides a significant additional information regarding the COP dynamic, relatively to other  
 360 features. Let  $v = (v_1, v_2)$  denote the eigenvector associated with the highest variance produced by a PCA of  
 361 the COP bi-dimensional signal  $(X_n, Y_n)_{1 \leq n \leq N}$ . Then the principal sway direction is defined as:

$$362 \text{ SWAY DIRECTION} \quad \arccos\left(\frac{|v_2|}{\sqrt{v_1^2 + v_2^2}}\right) \times \frac{180}{\pi}$$

363 An illustration of the calculation of this feature is shown in Figure 2.

### 364 3.3 Dynamic variables

365 These descriptors are based on the local displacements of the COP trajectory. Most of them revolve around  
 366 the quantification of the velocity of the signal, and consequently, are sensitive to additive noise, such as elec-  
 367 tromagnetic noise, and variation of the sampling frequency (see e.g. [Press and Teukolsky, 1990, Schubert

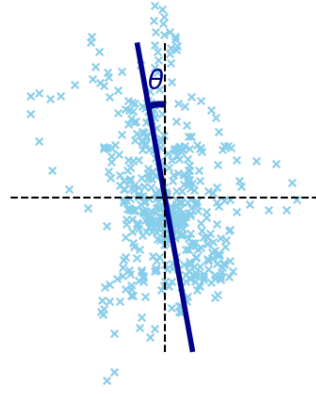


Figure 2: Illustration of the calculation of the principal sway direction. The feature is equal to the angle  $\theta$

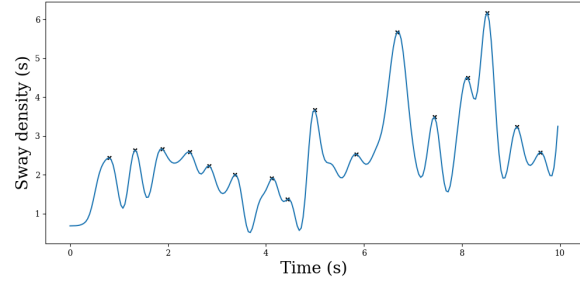
Feature	Full Name	Formula	Units
SWAY LENGTH ML	Sway Length ML	$\sum_n  X_{n+1} - X_n $	cm
SWAY LENGTH	Total Sway Length	$\sum_n \sqrt{(X_{n+1} - X_n)^2 + (Y_{n+1} - Y_n)^2}$	cm
MEAN SPD ML	Average Velocity ML	SWAY LENGTH ML/T	cm.s <sup>-1</sup>
MEAN SPD	Average Velocity	SWAY LENGTH/T	cm.s <sup>-1</sup>
AREA PER SEC.	Sway Area per sec.	$\frac{1}{2T} \sum_n  X_{n+1}Y_n - X_nY_{n+1} $	cm <sup>2</sup> .s <sup>-1</sup>
STD SPD ML.	Deviation Velocity ML	$\sqrt{\frac{1}{N} \sum_n (V_n^x - \bar{V}^x)^2}$	cm.s <sup>-1</sup>
STD SPD.	Deviation Velocity	$\sqrt{\frac{1}{N} \sum_n (V_n - \bar{V})^2}$	cm.s <sup>-1</sup>
PHASE PLANE ML	ML Phase Plane Parameter	$\sqrt{\text{RMS ML}^2 + \text{STD SPD ML}^2}$	*
VFY	-	STD SPD <sup>2</sup> /MEAN AP	cm.s <sup>-2</sup>
LFS	Length over Area	$\frac{\text{SWAY LENGTH}}{95\% \text{ CONF. AREA}}$	cm <sup>-1</sup>
FRACTAL DIM	Fractal Dimension	see Def. Fractal Dimension	-
SET OF ZERO CROSS. ML	Set of Zero Crossings ML	$\mathcal{Z}^{V^x}$	-
ZERO CROSS. ML	Number of Zero Crossings ML	$\#\mathcal{Z}^{V^x}$	-
PEAK VEL. + ML	Mean Positive Peak of ML Vel.	see Def.	cm.s <sup>-1</sup>
PEAK VEL. - ML	Mean Negative Peak of ML Vel.	see Def.	cm.s <sup>-1</sup>
PEAK VEL. ML	Mean Peak of ML Velocity	$\frac{1}{K} \sum_\ell p_\ell^{V^x}$	cm.s <sup>-1</sup>
PEAK SD	Mean Peak of Sway Density	$\frac{1}{K} \sum_\ell p_\ell^{\text{SD}}$	s
DIST. PEAK SD	Mean Spatial Dist. between S.D. Peaks	see Def.	cm
MEAN FREQ. ML	Mean Frequency ml	$\frac{1}{4\sqrt{2}} \times \frac{\text{MEAN SPD ML}}{\text{MEAN DIST ML}}$	Hz
MEAN FREQ. ML-AP	Mean Frequency	$\frac{1}{4\sqrt{2}} \times \frac{\text{MEAN SPD}}{\text{MEAN DIST}}$	Hz

Table 4: Summary of the definition of the dynamic features. All the listed ML features can also be computed for the AP axis. For units, cm stands for centimeter, s for seconds, Hz for Hertz, and – for unitless. \* : this feature is obtained by summing non-homogeneous term, and therefore has no valid units.

et al., 2012]). Another quantity of interest for dynamic variables is the Sway Density, which is designed to encode the local stability of the COP signal. This is quantified by measuring around each point the number of consecutive points which lie in a circle of a certain radius. This count is then divided by the sampling frequency. In this study we choose to use a radius of 3mm, as it has been shown that the choice of the radius is not critical and that a value between 3 and 5 mm is adequate for most applications [Jacono et al., 2004].



(a) Illustration of the computation of the sway density at time  $t$ . In this example, four consecutive points fall in the circle of radius  $3mm$ , therefore the sway density at time  $t$  is equal to  $4/F_s$



(b) Example of filtered trajectory of the sway density over time. The black crosses indicate the position of peaks identified using Definition 2

Figure 3: Illustration of the sway density computation and the peaks computation

**Definition 1** (Sway Density). *The Sway Density at time  $n\Delta_t$  is defined as*

$$SD_n = \frac{SD_n^{(+)} + SD_n^{(-)}}{F_s}$$

373 where

$$SD_n^{(+)} = \max \{q \geq 0, \forall p \leq q, \sqrt{(X_{n+p} - X_n)^2 + (Y_{n+p} - Y_n)^2} \leq 3mm\}$$

$$SD_n^{(-)} = \max \{q \geq 0, \forall p \leq q, \sqrt{(X_{n-p} - X_n)^2 + (Y_{n-p} - Y_n)^2} \leq 3mm\}$$

374 **Definition 2** (Peaks of sway density). *To compute the peaks of the sway density, the signal is first low-pass*  
 375 *filtered at 2.5 Hz with a Butterworth filter of order 4 [Jacono et al., 2004]. Let  $\widetilde{SD}_n$  represent the sway density*  
 376 *signal obtained after filtering. Then, the peaks of  $SD_n$  are defined as the local maximum of the filtered signal,*  
 377 *i.e. they occur at the indices in  $\{n_{p_1}^S, \dots, n_{p_K}^S\}$  such that for all  $k \in \{1, \dots, K\}, 1 < n_{p_k}^S < N, \widetilde{SD}_{n_{p_k}^S} >$*   
 378  *$\widetilde{SD}_{n_{p_k}^S - 1}$  and  $\widetilde{SD}_{n_{p_k}^S} > \widetilde{SD}_{n_{p_k}^S + 1}$ .*

379 *An example of peaks identified on a sway density signal is shown in Figure 3b.*

380 **Computing Velocity** The COP trajectory recorded using force platforms is by nature a noisy signal. To  
 381 address this problem, common preprocessing methods, such as low pass filters, are used to remove the high  
 382 frequency components of the noise. However, there is no consensus on the frequency threshold that separates  
 383 body sway from sensor noise. For instance, values of 5, 10 and 20 Hz have been proposed by [Geurts et al.,  
 384 1993, Hernandez et al., 2015, Huurnink et al., 2013]. This choice has a significant impact on the computation  
 385 of the COP velocity, in particular when using discrete derivative formula. Therefore, and to limit the influence  
 386 of the hyperparameters and the force platform characteristics, it is important to use robust methods such as  
 387 spline interpolation or Savitzky-Golay filters to differentiate the signal [Press and Teukolsky, 1990, Savitzky  
 388 and Golay, 1964, Curtain and Pritchard, 1977].

**Notation** In the following,  $\mathbf{V}^x = (\mathbf{V}_n^x)_{1 \leq n \leq N}$  and  $\mathbf{V}^y = (\mathbf{V}_n^y)_{1 \leq n \leq N}$  represent the estimations of the COP velocities in the ML and AP axis, respectively. In our experiments, they are computed using a Savitzky-Golay filter with a polynomial of order 3 and a filter window of length 5.  $\mathbf{V}$  represents the norm of the velocity, i.e. for each  $1 \leq n \leq N$ ,

$$\mathbf{V}_n = \sqrt{(\mathbf{V}_n^x)^2 + (\mathbf{V}_n^y)^2}$$

389 The mean values of  $\mathbf{V}^x$ ,  $\mathbf{V}^y$  and  $\mathbf{V}$  are respectively denoted by  $\overline{\mathbf{V}^x}$ ,  $\overline{\mathbf{V}^y}$  and  $\overline{\mathbf{V}}$ .

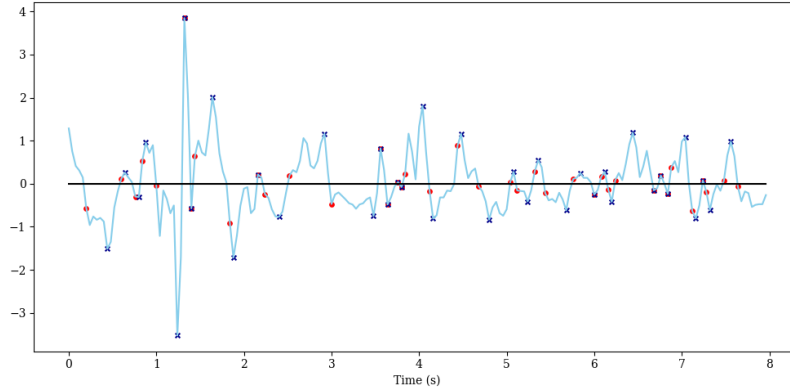


Figure 4: An example of velocity signal. The red dots indicate zero crossings identified using Definition 3 and the black crosses indicate the position of peaks identified using Definition 4

**Definition 3** (Zero crossing points of velocity).

Let  $V = (V_n)_{1 \leq n \leq N}$  stand for the velocity signal in the ML or AP axis. The zero crossing points  $z_1, \dots, z_J$ , are the variables in  $\{1, \dots, N\}$  verifying the following conditions:

1. For all  $\ell \in \{1, \dots, J\}$ ,  $V_{z_{\ell-1}} \times V_{z_{\ell}} \leq 0$  and  $V_{z_{\ell}} \neq 0$
2.  $V_{z_1} \times V_{n_0} < 0$  and for all  $\ell \in \{2, \dots, J\}$ ,  $V_{z_{\ell}} \times V_{z_{\ell-1}} < 0$

**Definition 4** (Peaks of velocity).

Let  $V = (V_n)_{1 \leq n \leq N}$  stand for  $V^x$  or  $V^y$ . Let  $z_1, \dots, z_J$  be the zero crossing points of  $V$ . Then for all  $1 \leq \ell \leq K = J - 1$ , the  $\ell$ -th peak of  $V$  occurs at the sampling variable  $n_{p_{\ell}^V}$  and is equal to  $p_{\ell}^V$ , where  $n_{p_{\ell}^V} = \arg \max_{n \in \{1, \dots, N\}, z_{\ell} \leq n \leq z_{\ell+1} - 1} |V_n|$  and  $p_{\ell}^V = V_{n_{p_{\ell}^V}}$ . An example of peaks identified on a velocity signal is shown in Figure 4.

**Mean Velocity (Normalized Sway Length, Sway Path)**

The mean velocity of the COP is one of the most widely used variables. Overall, the mean velocity is considered as one of the most reliable feature, especially in the AP direction [Low et al., 2017]. This variable has been shown to be influenced by age-related postural alterations, under both eyes-open and eyes-closed conditions [Prieto et al., 1993, 1996] and to be predictive of the risk of falling [Howcroft et al., 2017]. Indeed, the COP movement velocity was significantly correlated to age-related neuromuscular phenomena such as loss of plantar flexor muscle volume [Kouzaki and Masani, 2012], tremors [Kouzaki and Masani, 2012] or an increase of the co-contraction strategy of agonist and antagonist muscles of the leg [Benjuya et al., 2004, Carpenter et al., 2001a, Ho and Bendrups, 2002, Nelson-Wong et al., 2012]. The perception of the COP movement velocity could be an important factor in the control of ankle extensor activity through anticipatory strategies [Masani, 2003, Sun et al., 2019], highlighting the impact of age-related neuromuscular deterioration on static balance, with significant differences between eyes open or closed conditions [Howcroft et al., 2015] and more generally on the risk of falling [Brauer et al., 2000, Kwok et al., 2015]. For a constant sampling interval, the mean velocity is defined as the sum of the distances between consecutive points, also called sway length, divided by the duration of the recording. Therefore, the mean velocity can be seen as a normalized version, with respect to the duration, of the sway length, which has been previously cited as the most common feature in the literature to evaluate the effect of exercise interventions [Low et al., 2017], and has been shown to distinguish people at risk of falling from healthy people [Kantner et al., 1991].

$$\text{SWAY LENGTH ML} \quad \sum_{n=1}^{N-1} |X_{n+1} - X_n|$$

$$\text{SWAY LENGTH AP} \quad \sum_{n=1}^{N-1} |Y_{n+1} - Y_n|$$

$$\text{SWAY LENGTH} \quad \sum_{n=1}^{N-1} \sqrt{(X_{n+1} - X_n)^2 + (Y_{n+1} - Y_n)^2}$$

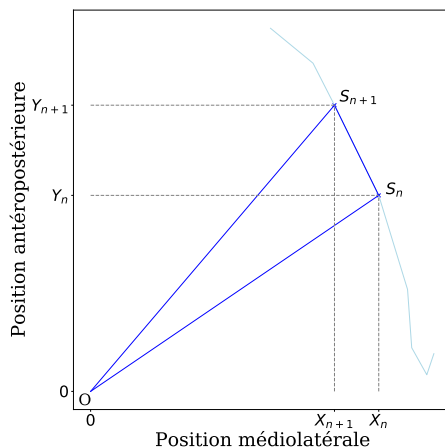


Figure 5: The sway area per second sums the area of the successive triangles  $OS_nS_{n+1}$  formed at each time  $n$  by the points of the signal and the center of the trajectory  $O$ . The figure shows in blue the triangle formed at a specific time for a centered trajectory.

421 MEAN SPD ML  $\frac{\text{SWAY LENGTH ML}}{T}$

422 MEAN SPD AP  $\frac{\text{SWAY LENGTH AP}}{T}$

423 MEAN SPD  $\frac{\text{SWAY LENGTH}}{T}$

424 Note that it is also possible to compute the mean velocity differently, using the Savitzky-Golay derivative  
 425 previously discussed in the paragraph *Computing Velocity*. While not mathematically equivalent, these two  
 426 definitions lead to similar values of mean velocity, as the average operator is robust to smooth interpolation  
 427 such as Savitzky-Golay filters. Therefore we present here the normalized sway length formulation, which is  
 428 frequently used in clinical studies [Low et al., 2017].

429 **Sway Area per second** This variable evaluates the average area circumscribed by the COP for each one  
 430 second time interval. The interval duration used for its calculation may vary between studies [Hufschmidt  
 431 et al., 1980], and is not always clearly stated in the literature [Maranesi et al., 2016]. The sway area per second  
 432 is computed by adding the area of the triangles whose vertices are two consecutive points of the COP trajectory  
 433 and the mean position of the COP [Prieto et al., 1996, Hufschmidt et al., 1980]. Figure 5 shows an example  
 434 of the triangle formed at a specific time for a real signal. This feature has been shown to significantly differ  
 435 between non-fallers and fallers [Maranesi et al., 2016, Lichtenstein et al., 1988, Pajala et al., 2008].

436 AREA PER SEC.  $\frac{1}{2T} \sum_{n=1}^{N-1} |X_{n+1}Y_n - X_nY_{n+1}|$

437 **Phase plane parameter** This feature is thought to express the dispersion of both the velocity and the position  
 438 of the COP [Riley et al., 1995]. It has been claimed that this variable provides insight into this dynamic  
 439 aspect of balance control, and significantly differs between young healthy and elderly participants [Raymakers  
 440 et al., 2005]. Moreover the phase plane parameter has been found to be reliable in both open and close eyes  
 441 conditions [Qiu and Xiong, 2015, Moghadam et al., 2011]. However it should be noted that the two terms  
 442 that are added together, the standard deviation of position and the standard deviation of velocity, are not  
 443 homogeneous.

444 STD SPD ML  $\sqrt{\frac{1}{N} \sum_{n=1}^N (V_n^x - \bar{V}^x)^2}$

445 STD SPD AP  $\sqrt{\frac{1}{N} \sum_{n=1}^N (V_n^y - \bar{V}^y)^2}$

$$446 \text{ PHASE PLANE ML} \quad \sqrt{\text{RMS ML}^2 + \text{STD SPD ML}^2}$$

$$447 \text{ PHASE PLANE AP} \quad \sqrt{\text{RMS AP}^2 + \text{STD SPD AP}^2}$$

448 **VFY**<sup>1</sup> [Gagey and Gentaz, 1993] first defined this parameter as the variance of the COP velocity divided  
 449 by the mean position of the COP on the AP axis, but this definition was contested by more recent work  
 450 [Gagey, 1999]. However, this definition is still commonly used (see e.g. [Aufauvre et al., 2005]), therefore we  
 451 chose to report it below. The VFY could correlated with the tension of the posterior leg muscles (due to both  
 452 viscoelasticity and basic tone) [de Tausia et al., 2010, Gagey and Gentaz, 1993] but the link with physiology  
 453 has yet to be demonstrated. Importantly, the VFY suffers from the same drawback as the mean value does, due  
 454 to the variability in the placement of the feet on the force platform [Duarte and Freitas, 2010].

$$455 \text{ STD SPD} \quad \sqrt{\frac{1}{N} \sum_{n=1}^N (V_n - \bar{V})^2}$$

$$456 \text{ VFY}^1 \quad \frac{\text{STD SPD}^2}{\text{MEAN AP}}$$

457 **Length Over Area (LFS)** In [Aufauvre et al., 2005] the length over area is defined as the total length of the  
 458 sway path over the surface of the circumscribing area (circle or ellipse). In their study, the authors did not find  
 459 any significant difference between fallers and non fallers for this variable, or according to whether the eyes  
 460 were open or closed. [Kim et al., 2019] have shown that the length over area was correlated in eyes closed  
 461 condition with mild-to-moderate traumatic brain injury, showing an poorest balance control when the white  
 462 matter trauma is more severe.

$$463 \text{ LFS} \quad \frac{\text{SWAY LENGTH}}{95\% \text{ CONF. AREA}}$$

464 **Fractal Dimension** The fractal dimension is a unitless measure of the degree to which a curve fills the space  
 465 it is embedded in [Prieto et al., 1996]. Previous works have claimed that the fractal dimension of the COP is  
 466 one of the most reliable sway variable for differentiating among age groups and pathologies [Myklebust et al.,  
 467 1995]. Three main methods are used to compute the fractal dimension [Prieto et al., 1996]. In a first model,  
 468 the area of the stabilogram is approximated using a circle including all the points of the COP trajectory, which  
 469 generally over estimates the area enclosed by the signal [Prieto et al., 1996]. In the two other methods, the area  
 470 is computed using either a confidence circle or a confidence ellipse. We present hereafter the formula using  
 471 the confidence ellipse, which is more flexible. The value of the fractal dimension could increase in healthy  
 472 adults when the eyes are closed [Tassani et al., 2019] or when wearing orthopaedic insoles [Bateni, 2013].  
 473 Significantly higher values were found in young participants than in elderly people during eyes open recording  
 474 [Qiu and Xiong, 2015]. These findings are more in line with an improvement in stability as the value of the  
 475 fractal dimension increases.

$$476 \text{ FRACTAL DIM} \quad \frac{\log N}{\log N + \log \sqrt{\frac{4}{\pi}} \times 95\% \text{ CONF. AREA} - \log \text{SWAY LENGTH}}$$

477 **Zero Crossing (of Velocity)** This variable is defined as the number of times that the COP velocity crosses  
 478 the zero value axe [Jeong et al., 2007]. Tuunainen et al. indicated that "zero crossing velocity showed a high  
 479 rate of velocity change around the neutral position of stance" [Tuunainen et al., 2013]. The latter found an  
 480 association between this variable and falls, but no significant difference between fallers and non-fallers, which  
 481 is in line with previous results that found no significant difference, even when comparing the two groups of  
 482 older people to healthy subjects [Hewson et al., 2010]. Let  $\mathcal{Z}^{V^x}$ ,  $\mathcal{Z}^{V^y}$  denote the sets of zero crossing points of  
 483  $V^x$ , respectively  $V^y$ , given by Definition 3. The zero crossing variables represent the number of zero crossing  
 484 points in each direction:

$$485 \text{ ZERO CROSS. ML} \quad \#\mathcal{Z}^{V^x}$$

$$486 \text{ ZERO CROSS. AP} \quad \#\mathcal{Z}^{V^y}$$

<sup>1</sup>This definition is contested, see e.g [Gagey, 1999]



487 **Mean Velocity Peak** A velocity peak has been defined as the maximal value between two zero crossing points  
 488 [Hewson et al., 2010]. The positive peaks of velocity, which correspond to displacements forward and to the  
 489 right in the AP and ML axis respectively, may be considered separately from negative peaks, which correspond  
 490 to displacements backward and to the left in the AP and ML axis respectively. The mean AP velocity peak  
 491 has been shown to discriminate between elderly fallers and non-fallers [Hewson et al., 2010]. An increase in  
 492 the absolute value would indicate poorest postural control. The zero crossing velocity variables are correlated  
 493 with each other in each direction ( $R=0.88$ ) but may be more weakly correlated with other variables, especially  
 494 with positional variables ( $R<0.8$ ), in the older population [Rasku et al., 2012]. Peak COP velocity has also  
 495 been previously correlated to the severity of knee osteoarthritis during the transition task from double-leg to  
 496 single-leg standing [Sabashi et al., 2021].

$$497 \text{ PEAK AP VEL. + ML } \frac{\sum_{\ell=1}^K p_{\ell}^{V^x} \times \mathbb{1}_{\{p_{\ell}^{V^x} > 0\}}}{\sum_{\ell=1}^K \mathbb{1}_{\{p_{\ell}^{V^x} > 0\}}}$$

$$498 \text{ PEAK AP VEL. - ML } \frac{\sum_{\ell=1}^K p_{\ell}^{V^x} \times \mathbb{1}_{\{p_{\ell}^{V^x} < 0\}}}{\sum_{\ell=1}^K \mathbb{1}_{\{p_{\ell}^{V^x} < 0\}}}$$

$$499 \text{ PEAK AP VEL. ML } \frac{1}{K} \sum_{\ell=1}^K p_{\ell}^{V^x}$$

500 These variables are similarly defined in the AP axis through replacing  $V^x$  by  $V^y$

501 **Mean Sway Density Peak** With the idea that postural control in quiet standing is governed by two major  
 502 mechanisms (intrinsic feedback and anticipatory feedforward), previous studies have focused on structural  
 503 posturographic parameters. [Baratto et al., 2002] have proposed a model in which these mechanisms, modu-  
 504 lated by ankle muscle activation and the internal inverted pendulum model respectively, distinguish between  
 505 short and long term factors. From this hypothesis, they propose to analyse the Sway Density (SD), counting  
 506 the number of consecutive samples of the posturographic trajectory that, for each instant, fall within a circle  
 507 of given radius defined by the operator (typically between 3 and 5 mm [Jacono et al., 2004]). In the resulting  
 508 signal, the SD peaks (high values of the number of points in the circle) correspond to the moments when the  
 509 ankle torque and the associated motor control systems enable relatively stable COP displacements.

$$510 \text{ PEAK SD } \frac{1}{K} \sum_{\ell=1}^K p_{\ell}^{SD}$$

511 **Mean Spatial Distance Between Sway Density Peaks** While peaks of SD correspond to relatively stable  
 512 COP displacements, valleys (low values of SD) are interpreted as destabilization phases in which the ankle  
 513 torque rapidly changes from one stable state to another, similarly to a micro-fall. Hence, the distance between  
 514 two consecutive peaks in the SD represent a micro-fall or a period of destabilization for [Baratto et al., 2002].  
 515 This saccade could correspond to the amplitude of the posturographic command or "the amount of change in  
 516 torque required for stabilization" [Vieira et al., 2009b]. The values of the "jump" from one posturographic  
 517 target to the next can be averaged to compute the mean spatial distance between peaks. The mean distance  
 518 between peaks seems to increase significantly when the eyes are closed [Kim et al., 2012, Vieira et al., 2009b],  
 519 in old age [Kim et al., 2012] or with history of past falls [Audiffren et al., 2016, Maranesi et al., 2016].

$$520 \text{ DIST. PEAK SD } \frac{1}{K} \sum_{\ell=1}^K \sqrt{(X_{\tau_{\ell+1}} - X_{\tau_{\ell}})^2 + (Y_{\tau_{\ell+1}} - Y_{\tau_{\ell}})^2}$$

521 **Mean Frequency** The mean frequency is defined by [Prieto et al., 1996] as the rotational frequency, consid-  
 522 ering the total length of the COP as a trajectory around a circle with a radius equals to the mean distance. This  
 523 variable is proportional to the ratio of the mean velocity to the mean distance, which has been studied in [Huf-  
 524 schmidt et al., 1980]. In [Maki et al., 1994], the mean frequency does not significantly differ between fallers  
 525 and non-fallers in prospective follow-up. This result is in line with other studies on then retrospective evalua-  
 526 tion of falls [König et al., 2014, Maranesi et al., 2016]. However, it has been argued that MEAN FREQUENCY,

527 especially in the AP direction, can be used to distinguishing elderly fallers from non-fallers [McGrath et al.,  
528 2012], and is reliable [Qiu and Xiong, 2015].

$$529 \text{ MEAN FREQ. ML} \quad \frac{1}{4\sqrt{2}} \times \frac{\text{MEAN SPD ML}}{\text{MEAN DIST ML}}$$

$$530 \text{ MEAN FREQ. AP} \quad \frac{1}{4\sqrt{2}} \times \frac{\text{MEAN SPD AP}}{\text{MEAN DIST AP}}$$

$$531 \text{ MEAN FREQ. ML-AP} \quad \frac{1}{2\pi} \times \frac{\text{MEAN SPD}}{\text{MEAN DIST}}$$

### 532 3.4 Frequency variables

Feature	Full Name	Formula	Units
TOTAL POWER ML	Total Power ML	$\sum_{k=k_{\text{inf}}}^{k_{\text{sup}}} \Gamma_k^X$	cm <sup>2</sup>
50 % POWER FREQ ML	Median of PSD ML	$\inf \left\{ k^* \in \mathbb{N}, \sum_{k=k_{\text{inf}}}^{k^*} \Gamma_k^X \geq 0.5 \sum_{k=k_{\text{inf}}}^{k_{\text{sup}}} \Gamma_k^X \right\} \times \frac{F_s}{N}$	Hz
95 % POWER FREQ ML	95% percentile of PSD ML	$\inf \left\{ k^* \in \mathbb{N}, \sum_{k=k_{\text{inf}}}^{k^*} \Gamma_k^X \geq 0.95 \sum_{k=k_{\text{inf}}}^{k_{\text{sup}}} \Gamma_k^X \right\} \times \frac{F_s}{N}$	Hz
POWER MODE ML	Mode of PSD	$\frac{F_s}{N} \times \arg \max_{k_{\text{inf}} \leq k \leq k_{\text{sup}}} \Gamma_k^X$	Hz
CENTROIDAL FREQ ML	Centroidal Frequency ML	$\sqrt{\frac{M_2^X}{M_0^X}}$	Hz
FREQ. DISP. ML	Frequency Dispersion ML	$\sqrt{1 - \frac{(M_1^X)^2}{M_2^X M_0^X}}$	-
ENERGY $\leq 0.5$ HZ ML	Energy Content below 0.5Hz ML	$\sum_{f_{\text{inf}} < f_k \leq 0.5} \Gamma^X(f_k)$	cm <sup>2</sup>
ENERGY 0.5-2 HZ ML	Energy Content 0.5-2Hz ML	$\sum_{0.5 < f_k \leq 2} \Gamma^X(f_k)$	cm <sup>2</sup>
ENERGY $> 2$ HZ ML	Energy Content above 2Hz ML	$\sum_{2 < f_k \leq f_{\text{sup}}} \Gamma^X(f_k)$	cm <sup>2</sup>
FREQ. QUOTIENT ML	Frequency Quotient	$\frac{\sum_{2 < f_k \leq 5} \Gamma^X(f_k)}{\sum_{f_{\text{inf}} < f_k \leq 2} \Gamma^X(f_k)}$	-

Table 5: Summary of the definitions of the frequency features. All the listed features can also be computed for the AP coordinates. For units, cm stands for centimeter, Hz for Hertz, and – for unitless.

533 This category is similar to the one presented in [Prieto et al., 1996], and includes the variables used to de-  
534 scribe the Power Spectral Density of the COP trajectory. Similarly to the dynamic variables, these descriptors  
535 are influenced by the sampling frequency of the force platform as well as the signal preprocessing.

**Notation** In the following,  $\Gamma_k^X = \Gamma^X(f_k)$  denotes the Power Spectral Density (PSD) coefficient of  $X$  corresponding to the frequency  $f_k = k \frac{F_s}{N}$ , for  $k \in \{1, \dots, N/2\}$  if  $N$  is even,  $k \in \{1, \dots, (N-1)/2\}$  otherwise. The frequency-domain measures are calculated for the frequency range from  $f_{\text{inf}} = 0.15 \text{ Hz}$  to  $f_{\text{sup}} = 5 \text{ Hz}$ , which corresponds to variables  $k_{\text{inf}} = \lfloor 0.15 \frac{N}{F_s} \rfloor + 1$  and  $k_{\text{sup}} = \lfloor 5 \frac{N}{F_s} \rfloor$ , an interval likely to provide significant information about the postural control system [Prieto et al., 1996]. We denote by

$$M_\ell^X = \sum_{k=k_{\text{inf}}}^{k_{\text{sup}}} f_k^\ell \Gamma_k^X$$

536 the  $\ell$ -th moment of the PSD.  $\Gamma_k^Y$  and  $M_\ell^Y$  are defined similarly. In our experiments, we estimate the PSD using  
537 Welch's method with 10 seconds segments, with 50% overlapping and linear detrending [Vieira et al., 2009a].

538 **Total Power** The total power is the energy contained in the entire power spectrum [Prieto et al., 1996].  
 539 Previous works have shown that the TOTAL POWER may be significantly larger in elderly participants compared to  
 540 young adults [Loughlin and Redfern, 2001, Kim et al., 2010]. In both groups, TOTAL POWER seems positively  
 541 correlated with height and be also dependant of the base-of-support in ML direction [Chiari et al., 2002, Kim  
 542 et al., 2014b].

543 TOTAL POWER ML 
$$\sum_{k=k_{\text{inf}}}^{k_{\text{sup}}} \Gamma_k^X$$

544 The same feature is defined for the AP axis through replacing  $\Gamma_k^X$  by  $\Gamma_k^Y$ .

545 **Quantiles of PSD** [Baratto et al., 2002] have shown that the frequency containing approximately 80% (from  
 546 70.7% to 95%) of the PSD may be of interest to the quantification of postural control. However these per-  
 547 centage values of interest vary significantly between studies. In [Maranesi et al., 2016] the authors proposed  
 548 the values from 50 to 95%, which were in turn used in [Howcroft et al., 2017]. In particular, the 50% power  
 549 frequency has been shown to be sensitive to muscle fatigue [Corbeil et al., 2003].

550 50% POWER FREQ. ML 
$$\inf \left\{ k^* \in \mathbb{N}, \sum_{k=k_{\text{inf}}}^{k^*} \Gamma_k^X \geq 0.5 \sum_{k=k_{\text{inf}}}^{k_{\text{sup}}} \Gamma_k^X \right\} \times \frac{F_s}{N}$$

551 95% POWER FREQ. ML 
$$\inf \left\{ k^* \in \mathbb{N}, \sum_{k=k_{\text{inf}}}^{k^*} \Gamma_k^X \geq 0.95 \sum_{k=k_{\text{inf}}}^{k_{\text{sup}}} \Gamma_k^X \right\} \times \frac{F_s}{N}$$

552 The same features are defined for the AP axis through replacing  $\Gamma_k^X$  by  $\Gamma_k^Y$ .

553 **PSD mode** The power spectrum density mode is the dominant frequency of the PSD [McClenaghan et al.,  
 554 1995]. This variable has previously been used to track changes in the physiological rhythm, under the assump-  
 555 tion that it would reflect modifications of the postural control strategy [Mackey and Glass, 1977, McClenaghan  
 556 et al., 1995, Williams et al., 1997]. This parameter showed no significant difference between fallers and non  
 557 fallers in either the AP or ML direction [Lajoie, 2004].

558 POWER MODE ML 
$$\frac{F_s}{N} \times \arg \max_{k_{\text{inf}} \leq k \leq k_{\text{sup}}} \Gamma_k^X$$

559 The same feature is defined for the AP axis through replacing  $\Gamma_k^X$  by  $\Gamma_k^Y$ .

560 **Centroidal Frequency and Frequency Dispersion** Both of these metrics measure the concentration of the  
 561 spectral mass in the PSD. The centroidal freq locates where the spectral mass is concentrated, and is defined  
 562 as the square root of the ratio of the second to the zeroth spectral moments. The frequency dispersion is  
 563 a measure of the variability in the frequency content of the power spectral density, ranging from zero (no  
 564 dispersion) to one (uniform spectral bandwidth) [Vanmarcke, 1972, Prieto et al., 1996]. In previous studies,  
 565 these two variables have been found to be not significantly different between young individuals and elderly  
 566 [Loughlin and Redfern, 2001].

567 CENTROIDAL FREQ ML 
$$\sqrt{\frac{M_2^X}{M_0^X}}$$

568 FREQ. DISP. ML 
$$\sqrt{1 - \frac{(M_1^X)^2}{M_2^X M_0^X}}$$

569 The same features are defined for the AP axis through replacing  $M_\ell^X$  by  $M_\ell^Y$ .

Feature	Full Name	Formula
SHORT-TERM DIFF. ML	Short term diffusion coefficient ML	$\exp(\hat{\alpha}_s^X)$
LONG-TERM DIFF. ML	Long term diffusion coefficient ML	$\exp(\hat{\alpha}_l^X)$
SHORT-TERM SCAL. ML	Short term Scaling coefficient ML	$\hat{\beta}_s^X/2$
LONG-TERM SCAL. ML	Long term Scaling coefficient ML	$\hat{\beta}_l^X/2$
CRIT. TIME ML	Critical Time ML	$\exp\left(\frac{\hat{\beta}_s^X - \hat{\beta}_l^X}{\hat{\alpha}_s^X - \hat{\alpha}_l^X}\right)$
CRIT. MSD ML	Critical MSD ML	$\hat{\alpha}_s^X \times \text{CRIT. TIME ML} + \hat{\beta}_s^X$

Table 6: Summary of the definition of the stochastic features. All the listed features can also be computed for the AP coordinates. Units are not reported since they are undefined in the stochastic models.

570 **Energy Content of Frequencies Intervals** The energy contents of particular frequency bands have raised  
571 significant interest in the evaluation of postural control. In [Soames and Atha, 1982], the energy content (in  
572 the AP direction) of the intervals 0.3-0.45 Hz, 0.6-0.75 Hz and 1.05-1.20 Hz were considered, while in the  
573 ML directions, the intervals were 0.30-0.45 Hz, 0.45-0.60 Hz and 0.75-0.90 Hz. Since then, other studies have  
574 proposed less granular intervals, to focus on low frequencies (between 0-2 Hz) and high frequencies (2-5Hz)  
575 [Bauer et al., 2010, 2016a, Aufaivre et al., 2005]. This difference is partly due to the population studied:  
576 while [Soames and Atha, 1982] have studied the balance of young, healthy people, the more recent studies  
577 were interested in older subjects. Similarly, [Baloh et al., 1998a] have proposed to study the quotient of the  
578 power of high frequencies (2-5Hz) over the power of low frequencies (0-2Hz). This quotient has been shown  
579 to significantly differ between young and elderly people [Baloh et al., 1994], and may be relevant to evaluate  
580 the influence of neurological impairment over postural control [Sullivan et al., 2006, 2010, 2015].

$$581 \text{ ENERGY } \leq 0.5 \text{ HZ} \quad \sum_{f_{\text{inf}} < f_k \leq 0.5} \Gamma^X(f_k)$$

$$582 \text{ ENERGY } 0.5\text{-}2 \text{ HZ} \quad \sum_{0.5 < f_k \leq 2} \Gamma^X(f_k)$$

$$583 \text{ ENERGY } > 2 \text{ HZ} \quad \sum_{2 < f_k \leq f_{\text{sup}}} \Gamma^X(f_k)$$

$$584 \text{ FREQ. QUOTIENT} \quad \frac{\sum_{2 < f_k \leq 5} \Gamma^X(f_k)}{\sum_{f_{\text{inf}} < f_k \leq 2} \Gamma^X(f_k)}$$

585 The same features are defined for the AP axis through replacing  $\Gamma_k^X$  by  $\Gamma_k^Y$ .

### 586 3.5 Stochastic variables

587 The variables of this category are derived from stochastic models of the COP. The descriptors presented  
588 originate from the seminal work of [Collins and De Luca, 1993], which introduced the idea of the SDA.

589 **Stabilogram Diffusion Analysis** In [Collins and De Luca, 1993], the authors have suggested that the COP  
590 quadratic displacement is similar to the one of a fractional Brownian motion with two regimes. This claim was  
591 based on the analysis of the Mean square Displacement (MSD) defined as follows:

**Definition 5 (MSD).** For any  $0 \leq \Delta t \leq \Delta t_N = T/3$ , the mean square displacement of the COP along the ML axis on the time interval  $\Delta t$  is defined as

$$MSD^X(\Delta t) = \frac{1}{N - F_s \Delta t} \sum_{n=1}^{N - F_s \Delta t} (X_{n + F_s \Delta t} - X_n)^2$$

592 This function can be similarly defined for the AP axis with  $Y$ .

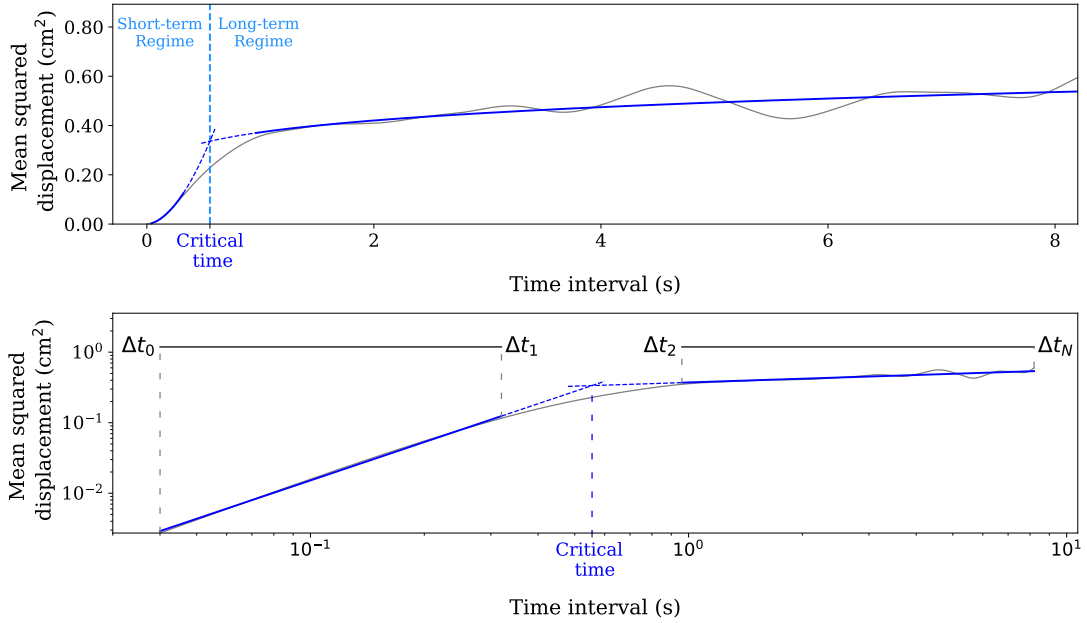


Figure 6: Example of Stabilogram Diffusion Analysis and parameters estimation in each regime. The fitted functions in each region are drawn in blue. (Top) Curve of the MSD as a function of the time interval. (Bottom) Curve of the MSD as a function of the time interval on a logarithmic scale and intervals of time used for the estimation of the linear functions in each region.

593 The constraint  $\Delta t \leq T/3$  limits the definition of the MSD to time intervals shorter than one third of  
 594 the total duration, a necessary restriction to avoid unreliable results [Collins and De Luca, 1993]. In their  
 595 work, [Collins and De Luca, 1993] have noted that there exists a critical time  $\Delta t_c$  such that the curve of  
 596 the MSD variations with respect to  $\Delta t$  (called diffusion plot) can be split into two regions with very differ-  
 597 ent behaviors: a short-term region ( $\Delta t \leq \Delta t_c$ ) and a long-term region ( $\Delta t \geq \Delta t_c$ ) (see Figure 6). The  
 598 short-term and long-term regions are the expression of different behaviors of the dynamic on different time  
 599 scales: on short time scales, the system exhibits persistence, i.e. positive correlation between successive  
 600 displacements, and on longer time scales, the dynamic is anti-persistent, meaning that the successive dis-  
 601 placements are negatively correlated [Collins and De Luca, 1993]. Different interpretations have been made  
 602 following this observation. [Collins and De Luca, 1993] have claimed that it was the result of two differ-  
 603 ent postural control regimes: on short time scales, the system evolves in open-loop, whereas on longer  
 604 time scales, control is activated and produces postural adjustments. This conclusion has been however re-  
 605 futed by several authors, with the argument that a closed-loop continuous control model could reproduce  
 606 similar patterns of the diffusion plot [Peterka, 2000]. Several control models have been proposed to ex-  
 607 plain the phenomenon and there is no consensus on the true model of control which governs posture stabi-  
 608 lization [Collins and De Luca, 1993, Delignières et al., 2011, Peterka, 2000, Chow and Collins, 1995]. These  
 609 short-term and long-term regions can be characterized through the estimation of the parameters in a two-  
 610 regimes model of the *MSD*. For this purpose, we use the single model formulation proposed by [Chiari et al.,  
 611 2000]:

$$MSD^X(\Delta t) = \begin{cases} D_s \Delta t^{2H_s} & \text{for } \Delta t \leq \Delta t_c \text{ (short-term)} \\ D_\ell \Delta t^{2H_\ell} & \text{for } \Delta t \geq \Delta t_c \text{ (long-term)} \end{cases}$$

612 where  $H_s$  and  $H_\ell$  are the short and long-term scaling exponents and  $D_s$  and  $D_\ell$  can be seen as short and  
 613 long-term diffusion coefficients. Note that the model and the computation technique proposed in [Chiari et al.,  
 614 2000] are not exactly the same as the one formerly introduced in [Collins and De Luca, 1993], therefore the  
 615 resulting features are not directly comparable with the previous ones. However the general interpretation of  
 616 the variables remains similar.

617 **Diffusion and scaling coefficients** For parameters estimation, the two regimes (short-term and long-term) of  
 618 the MSD are approximated by two linear functions of the time interval on a logarithmic scale:

$$\ln MSD^X(\Delta t) = \begin{cases} \alpha_s^X \ln(\Delta t) + \beta_s^X & \text{for } \Delta t \in [\Delta t_0, \Delta t_1] \\ & \text{(1) short-term} \\ \alpha_\ell^X \ln(\Delta t) + \beta_\ell^X & \text{for } \Delta t \in [\Delta t_2, \Delta t_N] \\ & \text{(2) long-term} \end{cases}$$

619 If this model fitted perfectly the data, we could directly search for the time  $\Delta t_c$  which separates the diffusion  
 620 plot into two different linear regions. However, as stated in [Chiari et al., 2000], there exists for some tra-  
 621 jectories a transition region in the MSD curve which is not well fitted by a linear model. For this reason the  
 622 short-term regime is estimated on a first region  $[\Delta t_0, \Delta t_1]$  where  $\Delta t_0 = 1/F_s$  and  $\Delta t_1$  is defined in the range  
 623  $[0.3s, 2.5s]$  as the highest time stamp which minimizes the root mean square error (RMSE) in the Ordinary  
 624 Least Square (OLS) fit of the model (1), then the long-term regime is estimated on a second region  $[\Delta t_2, \Delta t_N]$   
 625 where  $\Delta t_N = T/3$  and  $\Delta t_2$  is defined in the range  $[0.3s, 2.5s]$  as the highest time stamp which minimizes  
 626 the mean square error in the Ordinary Least Square (OLS) fit of the model (2). An illustration of this estima-  
 627 tion can be found in Figure 6. Let  $\hat{\alpha}_s^X$ ,  $\hat{\alpha}_\ell^X$ ,  $\hat{\beta}_s^X$  and  $\hat{\beta}_\ell^X$  denote the OLS estimator of  $\alpha_s^X$ ,  $\alpha_\ell^X$ ,  $\beta_s^X$  and  $\beta_\ell^X$ ,  
 628 respectively. Then:

629 SHORT-TERM DIFF. ML  $\exp(\hat{\alpha}_s^X)$

630 LONG-TERM DIFF. ML  $\exp(\hat{\alpha}_\ell^X)$

631 SHORT-TERM SCAL. ML  $\frac{\hat{\beta}_s^X}{2}$

632 LONG-TERM SCAL. ML  $\frac{\hat{\beta}_\ell^X}{2}$

633 These indices are similarly defined for the AP axis through replacing  $X$  by  $Y$ .

634 In other words, the SDA models the CoP behavior on short and long-term scales as two distinct stochastic  
 635 processes. On the one hand, the diffusion coefficients are interpreted as the level of stochastic activity of the  
 636 process in the two control regimes, along the mediolateral and the anteroposterior axis [Melzer et al., 2010,  
 637 Collins and De Luca, 1993]. The short-term diffusion coefficient has been shown to differ significantly between  
 638 individuals who sustained injuries after falls compared to non fallers and fallers without injuries [Kurz et al.,  
 639 2013]. On the other hand, the scaling coefficients are thought to quantify the correlation of the increments  
 640 of the process in its persistent (short-term) and its anti-persistent (long-term) regimes, along the mediolateral  
 641 and the anteroposterior axis. In practice, the scaling coefficients generally appear to satisfy  $H_s \geq 1/2$  and  
 642  $H_\ell \leq 1/2$ . Consequently, the short-term increments are considered to be positively correlated and the long-  
 643 term increments negatively correlated [Collins and De Luca, 1993]. The long-term scaling coefficient has been  
 644 shown to significantly differ between young individuals and elderly. [Muir et al., 2013],

645 **Critical time and Critical MSD** The critical time interval  $\delta_c$  is estimated as the value of  $\delta$  for which the  
 646 two linear functions in the logarithmic scale, (1) (short-term) and (2) (long-term), intersect. The critical mean  
 647 square displacement, is defined as the ordinate of the critical point, i.e. the value of the linear approximation  
 648 at the critical time interval [Melzer et al., 2010]. It represents the mean quadratic displacement covered in the  
 649 critical time interval, i.e. in a period of persistence. While these variables differ significantly between fallers  
 650 and non fallers in [Tuunainen et al., 2014] and between individuals who sustained injuries after falls compared  
 651 to non fallers and fallers without injuries in [Kurz et al., 2013], previous works have shown that these variables  
 652 have low reliability [Qiu and Xiong, 2015]. Moreover, these variables are uniquely derived from the other SDA  
 653 parameters and therefore with these additional features the model is not parcimonious [Chiari et al., 2000]. Let  
 654  $\hat{\alpha}_s^X$ ,  $\hat{\alpha}_\ell^X$ ,  $\hat{\beta}_s^X$  and  $\hat{\beta}_\ell^X$  denote the OLS estimator of  $\alpha_s^X$ ,  $\alpha_\ell^X$ ,  $\beta_s^X$  and  $\beta_\ell^X$ , respectively. Then:

655 CRIT. TIME ML  $\exp\left(\frac{\hat{\beta}_s^X - \hat{\beta}_\ell^X}{\hat{\alpha}_s^X - \hat{\alpha}_\ell^X}\right)$

656 Note that if the estimated critical time is larger than duration limit  $\Delta t_N$ , it is set at  $\Delta t_N$ . The critical mean  
657 square displacement is defined as

$$658 \text{ CRIT. MSD ML} \quad \hat{\alpha}_s^X \times \text{CRIT. TIME ML} + \hat{\beta}_s^X$$

659 Critical time and critical MSD are similarly defined for the AP axis with  $Y$ .

### 660 3.6 Descriptive analysis

661 Average values of the different variables, and their standard deviations, are reported in Table 7. Vari-  
662 ables that are strongly correlated to the total duration of the recording (such as LFS ML AND AP) are reported  
663 separately in the second part of the table. Interestingly, and despite the significant differences between the  
664 two datasets, the range of values obtained for were comparable for most variables. However, there are  
665 still some noticeable differences, particularly for the variables PEAK VELOCITY ML, TOTAL POWER ML,  
666 ENERGY CONTENT BELOW 0.5HZ ML and SHORT TIME DIFFUSION ML which show standard deviations  
667 higher than the means on the SmartCheck database. This is in line with previous works that have hypoth-  
668 esized that longer recording duration might be necessary for the proper evaluation of the power spectrum  
669 [Vieira et al., 2009b]. Moreover, the standard deviation of the variables is generally higher in the recordings  
670 from our protocol, which might result from both the shorter recording duration, and the more varied demo-  
671 graphics.

## 672 4 Discussion

673 The main objective of this review is to present the variables calculated from the stabilogram that are most  
674 commonly used in the analysis of balance in elderly participants prone or not to fall. The rationale of this  
675 approach is to propose a common framework for the analysis of COP displacements by presenting together  
676 the calculation methods and the values obtained on two different databases. In order to provide an explicit  
677 corpus, we relied on a recent systematic review with published methodology and broad selection criteria for  
678 the variables. The results of 70 variables are presented for two groups of participants aged 60 and over, with  
679 and without a history of falls. The means and standard deviations thus obtained make it possible to appreciate  
680 the homogeneity of the values despite significant differences in the recording protocols. The first protocol  
681 corresponds to a methodology easily applicable in routine consultations, while the other is more in line with  
682 the metrological standards of posturography.

### 683 4.1 Ageing and postural control

684 Falls in the older population are multifactorial in nature as they include socio-economic and environmen-  
685 tal elements in addition to biomedical factors. By providing a quantification of motor control in the elderly  
686 people, static posturography could help to determine a balance semiology [Nardone and Schieppati, 2010],  
687 especially for the most fragile people. This is particularly true since age-related sensorimotor altera-  
688 tions can impact motor functions and increase the risk of falling [Ambrose et al., 2015]. Static bal-  
689 ance is controlled in a complex way by different sensory (visual, vestibular, proprioceptive and tac-  
690 tile) and neuromotor systems (involving both sensory integration and movement planning to corti-  
691 cal control of standing and spinal reflex action resulting in changes in joint stiffness and damping)  
692 [Winter et al., 1998, Kang et al., 2013, Goodman and Tremblay, 2021]. Older people show altered motor  
693 strategies compared to young and healthy people, either for balance maintenance tasks or postural anticipation  
694 in the face of destabilisation [Woollacott and Manchester, 1993, Garcez et al., 2021]. But, in addition to the  
695 difficulty of studying the interactions between these systems and their actions in posture maintenance, there  
696 is a lack of interpretability of the COP variables [Palmieri et al., 2002], which is enhanced by the diversity of  
697 methods for calculating them. Finally, the choice of variables is difficult to justify from a physiological point  
698 of view [Chaudhry et al., 2011].

699 In the recent years, numerous methods have been proposed to analyse the trajectory of the COP, in order  
700 to investigate the differences between elderly fallers and non-fallers, as presented in our previous system-  
701 atic review [Quijoux et al., 2020]. At the same time, the univariate analysis of postural variables provides  
702 limited information on the physiological causes of falls [Duarte and Freitas, 2010]. This has encouraged  
703 the multiplication of variables, as it may be necessary to analyse all the components of the stabilogram –

	Mean $\pm$ std (WBB dataset)	Mean $\pm$ std (Public dataset)
mean distance ML	0.31 $\pm$ 0.25	0.24 $\pm$ 0.10
mean distance AP	0.53 $\pm$ 0.28	0.39 $\pm$ 0.19
mean distance Radius	0.68 $\pm$ 0.38	0.51 $\pm$ 0.22
maximal distance ML	1.21 $\pm$ 0.98	0.94 $\pm$ 0.40
maximal distance AP	1.89 $\pm$ 1.00	1.47 $\pm$ 0.65
maximal distance Radius	2.05 $\pm$ 1.16	1.58 $\pm$ 0.68
rms ML	0.40 $\pm$ 0.31	0.30 $\pm$ 0.12
rms AP	0.66 $\pm$ 0.35	0.49 $\pm$ 0.24
rms Radius	0.79 $\pm$ 0.44	0.59 $\pm$ 0.26
amplitude ML	2.08 $\pm$ 1.67	1.67 $\pm$ 0.69
amplitude AP	3.37 $\pm$ 1.79	2.64 $\pm$ 1.15
amplitude ML AND AP	3.59 $\pm$ 2.03	2.79 $\pm$ 1.20
quotient both direction ML AND AP	0.62 $\pm$ 0.29	0.66 $\pm$ 0.17
planar deviation ML AND AP	0.79 $\pm$ 0.44	0.59 $\pm$ 0.26
coefficient sway direction ML AND AP	0.01 $\pm$ 0.30	0.03 $\pm$ 0.20
confidence ellipse area ML AND AP	6.01 $\pm$ 9.35	3.02 $\pm$ 3.32
principal sway direction ML AND AP	17.91 $\pm$ 20.91	18.99 $\pm$ 11.57
mean velocity ML	0.83 $\pm$ 0.68	0.50 $\pm$ 0.22
mean velocity AP	1.60 $\pm$ 1.36	0.87 $\pm$ 0.39
mean velocity ML AND AP	1.97 $\pm$ 1.60	1.10 $\pm$ 0.47
sway area per second ML AND AP	0.48 $\pm$ 0.79	0.18 $\pm$ 0.20
phase plane parameter ML	1.20 $\pm$ 1.03	0.75 $\pm$ 0.31
phase plane parameter AP	2.23 $\pm$ 1.74	1.25 $\pm$ 0.55
peak velocity pos SPD ML	1.04 $\pm$ 0.98	0.65 $\pm$ 0.32
peak velocity neg SPD ML	1.05 $\pm$ 1.06	0.65 $\pm$ 0.33
peak velocity all SPD ML	1.05 $\pm$ 1.02	0.65 $\pm$ 0.33
peak velocity pos SPD AP	2.17 $\pm$ 2.12	1.19 $\pm$ 0.60
peak velocity neg SPD AP	2.14 $\pm$ 1.95	1.20 $\pm$ 0.64
peak velocity all SPD AP	2.16 $\pm$ 2.03	1.19 $\pm$ 0.62
mean peak Sway Density	1.05 $\pm$ 0.71	1.84 $\pm$ 0.92
mean distance peak Sway Density	0.59 $\pm$ 0.39	0.34 $\pm$ 0.20
mean frequency ML	0.52 $\pm$ 0.21	0.39 $\pm$ 0.13
mean frequency AP	0.56 $\pm$ 0.29	0.42 $\pm$ 0.15
mean frequency ML AND AP	0.48 $\pm$ 0.22	0.37 $\pm$ 0.12
total power ML	3.03 $\pm$ 8.22	2.14 $\pm$ 2.08
total power AP	6.33 $\pm$ 8.52	5.66 $\pm$ 10.22
power frequency 50 ML	0.42 $\pm$ 0.13	0.43 $\pm$ 0.14
power frequency 50 AP	0.37 $\pm$ 0.18	0.42 $\pm$ 0.13
power frequency 95 ML	1.16 $\pm$ 0.42	1.09 $\pm$ 0.23
power frequency 95 AP	1.33 $\pm$ 0.56	1.23 $\pm$ 0.24
frequency mode ML	0.32 $\pm$ 0.17	0.33 $\pm$ 0.18
frequency mode AP	0.25 $\pm$ 0.19	0.27 $\pm$ 0.14
centroid frequency ML	0.65 $\pm$ 0.18	0.61 $\pm$ 0.14
centroid frequency AP	0.69 $\pm$ 0.25	0.66 $\pm$ 0.14
frequency dispersion ML	0.61 $\pm$ 0.07	0.56 $\pm$ 0.06
frequency dispersion AP	0.65 $\pm$ 0.07	0.60 $\pm$ 0.05
energy content below 05 ML	2.23 $\pm$ 7.21	1.36 $\pm$ 1.75
energy content below 05 AP	4.23 $\pm$ 5.71	3.67 $\pm$ 8.47
energy content 05 2 ML	0.75 $\pm$ 1.27	0.76 $\pm$ 0.90
energy content 05 2 AP	1.83 $\pm$ 3.46	1.93 $\pm$ 2.23
energy content above 2 ML	0.05 $\pm$ 0.24	0.01 $\pm$ 0.01
energy content above 2 AP	0.26 $\pm$ 1.53	0.05 $\pm$ 0.07
frequency quotient ML	0.02 $\pm$ 0.02	0.01 $\pm$ 0.00
frequency quotient AP	0.03 $\pm$ 0.06	0.01 $\pm$ 0.01
short time diffusion ML	0.72 $\pm$ 1.44	0.32 $\pm$ 0.34
long time diffusion ML	0.36 $\pm$ 1.10	0.09 $\pm$ 0.14
critical time ML	0.54 $\pm$ 0.74	0.41 $\pm$ 0.22
critical displacement ML	0.31 $\pm$ 1.05	0.07 $\pm$ 0.14
short time scaling ML	0.83 $\pm$ 0.07	0.90 $\pm$ 0.03
long time scaling ML	0.17 $\pm$ 0.19	0.19 $\pm$ 0.10
short time diffusion AP	1.72 $\pm$ 2.53	0.80 $\pm$ 1.03
long time diffusion AP	0.88 $\pm$ 1.19	0.26 $\pm$ 0.59
critical time AP	0.68 $\pm$ 0.47	0.43 $\pm$ 0.24
critical displacement AP	0.81 $\pm$ 1.17	0.22 $\pm$ 0.58
short time scaling AP	0.81 $\pm$ 0.10	0.88 $\pm$ 0.03
long time scaling AP	0.08 $\pm$ 0.18	0.18 $\pm$ 0.12
<hr/>		
Duration sensitive variables	Mean $\pm$ std (WBB dataset)	Mean $\pm$ std (Public dataset)
LFS ML AND AP	14.49 $\pm$ 9.52	31.26 $\pm$ 14.83
fractal dimension ML AND AP	1.88 $\pm$ 0.23	1.98 $\pm$ 0.15
zero crossing SPD ML	127.43 $\pm$ 34.16	195.47 $\pm$ 32.94
zero crossing SPD AP	113.84 $\pm$ 31.43	200.08 $\pm$ 39.55

Table 7: Distribution of COP variables. For each variable, average values and standard deviations are reported in each dataset. WBB dataset refers to the data from our experiment, recorded with the Wii Balance Board and Public dataset refers to the open-access dataset of human balance [Santos and Duarte, 2016a]. Duration sensitive variables refer to variables that are strongly dependent on the duration of the recording.



704 in a particular axis and in two dimensions – to fully capture the COP dynamics and the age-related motor  
705 adaptations [Bargiotas et al., 2018]. Indeed, age-related decline in postural control is not uniform, which is  
706 understandable given the various anatomical structures that may be affected [Shaffer and Harrison, 2007].  
707 Distal myelin fibres and sensory receptors are affected by senescence and sedentary life, leading to im-  
708 paired proprioception, particularly in the hips, knees and ankles [Horak et al., 1989, Robbins et al., 1995],  
709 as well as loss of touch discrimination [Perry, 2006], with a potential predominance in the distal joints of  
710 the lower limb [Pickard et al., 2003, Shaffer and Harrison, 2007]. At the neuromuscular level, all the con-  
711 tractile properties of the muscles are impacted [Liu et al., 2005], notably by the reduction in the vascular  
712 feeding system and thus, in the number of muscle fibres, their volume and their contractibility. Presynap-  
713 tic inhibition of Ia afferents, which plays a role in leg muscle contractility, is more favoured in the elderly  
714 when sensory and somaesthetic afferents are reduced [Baudry and Duchateau, 2012]. This type of neuromus-  
715 cular alteration could partly explain the the adoption of a leg muscle co-contraction strategy in the elderly  
716 [Papegaaij and Hortobágyi, 2017]. This co-contraction may reduce the exploitation of proprioceptive afferents  
717 from the mechanoreceptors [Benjuya et al., 2004, Baudry, 2016, Craig et al., 2016] and the efficiency of the  
718 muscular efferents in the segmental control of balance [Finley et al., 2012, Nelson-Wong et al., 2012]. A sig-  
719 nificant correlation between the increase in co-contraction measured in the elderly and the increase in MAX AP  
720 was found, whereas it was absent in young adults [Baudry and Duchateau, 2012]. As a result, studies agree  
721 that an overall shift in balance control from spinal to supraspinal levels occurs in older adults, in line with  
722 what is found in healthy subjects when proprioceptive afferents decrease [Alizadehsaravi et al., 2020]. Given  
723 the diversity of disorders affecting the elderly, a bilateral alteration of the vestibular system could lead to an  
724 increase in the values of the COP variables, as seen on SWAY LENGTH [Mbongo et al., 2005]. When visual  
725 inputs are altered (with the use of a moving target), there is an increase in the contribution of the knee and hip  
726 joints, which correlate with an increase in COP variables in the elderly people [Freitas and Duarte, 2012]. An  
727 increase in the amplitude of displacement suggests a decrease in the ability to maintain a stable upright posi-  
728 tion, but the diversity of results obtained for positional and dynamic variables led Palmieri et al. to minimize  
729 their clinical interpretation [Palmieri et al., 2002]. Dynamic, frequency and stochastic variables could pro-  
730 vide complementary and clinically relevant information. Although more studies are needed before concluding  
731 on their physiological interpretation, we note that biomechanical modelling has shown a negative correlation  
732 between the supposed stiffness of the system and mean frequency and MEAN VELOCITY, but positive with  
733 CRITICAL TIME [Maurer and Peterka, 2005].

## 734 4.2 Feature classification

735 To the best of our knowledge, the classification of posturographic variables that is introduced in this study is  
736 new and differs from previous classification paradigms. [Duarte and Freitas, 2010] used a classification which  
737 distinguishes the descriptors resulting from a *structural analysis* – i.e. which aim to explain the control postu-  
738 ral commands through the behaviour of the COP, with sway density models or stochastic models – from other  
739 variables. In [Prieto et al., 1996], four categories of descriptors were proposed: (1) Time-Domain Distance  
740 measures, (2) Time-Domain Area measures, (3) Hybrid measures, and (4) Frequency-Domain measures. The  
741 first class includes features associated with either the displacement of the COP from the average, or the veloc-  
742 ity; the second gathers geometric approximations of the surface of the COP; the third includes combinations  
743 of distance measures [Prieto et al., 1996], which have been considered by others as dimensionless features  
744 [Qiu and Xiong, 2015]; the fourth contains variables related to the analysis of the power spectral density of the  
745 COP trajectory, usually obtained through Fast Fourier Transformation (FFT). Our classification, while similar  
746 to the one proposed in [Prieto et al., 1996], presents two major differences. First, since the work of [Prieto  
747 et al., 1996], popular stochastic models have been developed [Collins and De Luca, 1993, Duarte and Freitas,  
748 2010, Qiu and Xiong, 2015]. Hence we introduce a fourth category of variables, called Stochastic descriptors,  
749 which includes the features derived from stochastic based models of the COP. Second, we choose to regroup  
750 the non-stochastic, non-frequency derived descriptors into positional and dynamic classes. Importantly, this  
751 classification originated from signal processing concepts, and its main purpose was to ease the reading of this  
752 study.

## 753 4.3 Variables reliability

754 The reliability of stabilogram variables depends on several factors. The variation in the values of the  
755 posturographic variables recorded on the force platform reflect the participation of the muscles involved in  
756 maintaining balance and the contribution of the joints to postural oscillations. Feet placement could also

757 modify postural strategy in older population [Winter et al., 1996, Chiari et al., 2002]. For instance, when feet  
758 are joined, the ML displacements of the COP are mostly influenced by the hip adductors and abductors,  
759 whereas in the tandem position, movements in the ML direction are mostly related to the contractions of  
760 the invert and spurs muscles of the leg [Winter et al., 1996, 2003, Prince et al., 1995]. In the upright, straight  
761 position, feet open up by 45° apart, the movement in the ML direction is a mix of hip and ankle strategies,  
762 whereas the AP displacements are under the dominance of the ankle muscles.

763 Anthropometric factors influencing posturographic variables include height, weight, maximum foot width,  
764 base-of-support area, and foot opening angle as the relevant biomechanical variables [Chiari et al., 2002].  
765 The authors note a significant dependence of gender for the SWAY LENGTH, in the AP direction with  
766 eyes open. This could be explained by higher "height" and "weight" in males, with which the vari-  
767 ables are strongly positively correlated. As also mentioned by the authors, several ML variables, espe-  
768 cially positional (MEAN DISTANCE ML, SWAY LENGTH ML, RMS ML, RANGE ML), dynamic variables  
769 (MEAN VELOCITY ML) and frequentist variables (TOTAL POWER, FREQ. DISP. ML), decrease while base-  
770 of-support increase, in eyes open condition. Few frequentist variables are positively correlated with the  
771 size of the base-of-support (50 % POWER FREQ ML, 95 % POWER FREQ, CENTROIDAL FREQ ML). At  
772 the same time, the foot opening angle could have only a marginal or no impact on the variable values  
773 during open eyes recordings. The Maximum foot width showed a positive correlation for several fre-  
774 quentist variables but negative for the stochastic variables (notably SHORT TIME DIFFUSION COEFFICIENT,  
775 LONG TIME DIFFUSION COEFFICIENT and SHORT TIME SCALING DIFFUSION). These results illustrate the  
776 impact of morphological factors and foot position on the variables that vary within each family. It should  
777 be noted that these results are based on a signal filtered at 8 Hz and down-sampled at 20 Hz. Between ses-  
778 sions, posturographic variables have shown good reliability in the elderly people with the same experimental  
779 conditions [Li et al., 2016]. Riemann et al. have shown a better reliability of the variables when the position  
780 of the feet was left at the participant's choice, also considered as comfortable [Riemann and Piersol, 2017].  
781 Imposing a standardized foot placement could lead to a change of the biomechanics of the lower limb by  
782 reducing the number of degrees of freedom and hence, modify the strategy adopted to maintain balance  
783 [Gibbons et al., 2019]. Finally, the authors do not agree on a recommendation concerning the position of the  
784 feet and the width of the base-of-support, either by standardising them or by leaving it to the subject's choice  
785 of comfort, to increase the reliability of the measurements [Ruhe et al., 2010, Riemann and Piersol, 2017].

786 The differences between the values reported in the literature may also be explained by differences in equip-  
787 ment, sampling frequency, preprocessing and acquisition protocol [Carpenter et al., 2001b, Ruhe et al., 2010,  
788 Vieira et al., 2009b, Schmid et al., 2002]. First, the sampling frequency varies greatly between studies. The  
789 sampling frequency seems to have a greater impact on frequency variables than on positional and dynamic vari-  
790 ables. Rhea et al. add that a decrease in the sampling frequency (from 100 Hz to 25 Hz) has a non-significant  
791 impact on the non-linear analyses to obtain the stochastic variables [Rhea et al., 2015]. The reliability of the  
792 WBB, used in this study, has been widely studied in the literature and the authors generally conclude that it  
793 can be used to record balance [Clark et al., 2010, Bartlett et al., 2014, Abujaber et al., 2015, Severini et al.,  
794 2017]. However, we would emphasize the need to correct the sampling frequency of this force platform and  
795 refer the readers to our previous work for more details [Audiffren and Contal, 2016].

796 Secondly, the differences between preprocessing strategies that can be found in the literature may alter  
797 the computation of the parameters [Schmid et al., 2002], in particular for the dynamic group, as they involve  
798 the derivative of the trajectory and are sensitive to the cut-off frequency of applied filters. This led to the  
799 recommendation of a sampling frequency of 100 Hz and a cut-off frequency of 10 Hz, in the absence of  
800 further studies [Ruhe et al., 2010].

801 Thirdly, reliability may be affected by the acquisition protocol. It has been claimed that a sufficient record-  
802 ing duration, generally around 60 seconds, is required to obtain a robust estimation of the power spectral  
803 frequency [Vieira et al., 2009b]. The dynamic variables could show a greater reliability as the recording time  
804 is increased, up to 90 seconds, and then the benefit would be less noticeable [Ruhe et al., 2010]. However, the  
805 relevance of continuing the recordings beyond 60 seconds must be measured according to the population to be  
806 recorded because, on the one hand, good reliability has been obtained with dynamic and stochastic variables  
807 as early as 30 seconds [Caballero et al., 2015, Nagymáté et al., 2018] and the reproducibility of the variable  
808 measurements does not show the same dependence on the duration of recording according to the families of  
809 variables [Nejc et al., 2010], while on the other hand, proposing long recordings with several repetitions does  
810 not seem very feasible for measuring the balance in the clinical context, especially for extremely fragile people  
811 [Alsubaie et al., 2019]. Additionally, many of the parameters, such as the MEAN VALUE, RMS and all variables

812 derived from the power spectral density analysis, are based on the assumption that the center of pressure signal  
813 is stationary, which is generally not true [Strang et al., 2013]. This could significantly impact the variability of  
814 the parameters [Carroll and Freedman, 1993].

815 This influence of individual factors, experimental conditions and preprocessing methods on the values of  
816 the COP variables makes particularly essential studies reproducibility. which could be eased by the use of  
817 standardized definitions and implementation of the posturographic variables.

#### 818 **4.4 Scope and limitations**

819 This review focuses on the variables used to discriminate between elderly fallers and other older adults.  
820 However, in order to generalize the description of the variables, and more generally the mathematical require-  
821 ments for calculating them, it was necessary to extend the search to the references of the articles, which made  
822 it possible to highlight the reliability of several indices as well as their variability according to age. This review  
823 does not take into account indices that can be used to distinguish between younger and older participants and  
824 as such cannot be described as comprehensive. Many other posturographic variables have been proposed to  
825 assess the risk of falls in older people, either through measures of dynamic balance [Ringhof and Stein, 2018],  
826 or in correlation with clinical assessments of motor skills [Karlsson and Frykberg, 2000, Cheng et al., 2012],  
827 or because they are less commonly found in the literature, which did not fit the selection criteria of this review.  
828 Regarding the latter, we have not included variables based on biomechanical or other equilibrium modelling  
829 [McKee and Neale, 2019, Koltermann et al., 2020, Nicolai et al., 2021], as well as several other modelizations  
830 such as wavelet analyses [Chagdes et al., 2009], sample entropy analysis and other associated entropies com-  
831 putations [Gow et al., 2015, Degani et al., 2017] or analyses based on markov chains [Hur et al., 2012]. To  
832 overcome these limitations, further literature reviews should be conducted in the future to explore the most  
833 recent methods that have been applied to the postural signals. This would require going beyond the variables  
834 used to discriminate between fallers and non fallers.

835 We only present the calculation methods here, but the search for correlations between the risk of falling and  
836 these posturographic variables and their exploitation for prevention purposes leads to selection processes. Sev-  
837 eral models could be considered to identify the most relevant variables in the assessment of fall risk, whether  
838 using a Poisson regression [Palumbo et al., 2015] or zero-inflated models [Ullah et al., 2010] to describe the  
839 number of falls in a given time as well as other non-linear approaches with a selection process of the multi-  
840 ple variables as it was recently done in patients with Parkinson’s disease [Bargiotas et al., 2021] or between  
841 healthy fallers and non fallers [Audiffren et al., 2016].

842 The presentation of the values on the basis of two different recording protocols, and the similarity of the  
843 results obtained for these two populations, should enable more homogeneity in future studies, whilst the link  
844 between the physiology of static balance and these posturographic variables remains to be clarified.

## 845 **5 Conclusion**

846 A review of the literature on the analysis of the characteristics of the center of pressure for the discrim-  
847 ination of elderly people at high risk of falling revealed the lack of information concerning the methods of  
848 calculation of the posturographic variables used, as well as the lack of homogeneity and standardization be-  
849 tween studies. By presenting a comprehensive glossary of calculation methods and a library of functions that  
850 is as clear and exhaustive as possible, this should facilitate reproducibility between studies. Comparison with  
851 future studies should also be made easier by providing a basis for comparing these variables for two different  
852 protocol of COP recording, in elderly participants, with or without a history of falls. The choice of the selec-  
853 tion of variables among the growing number of possible methods of analysis of the COP trajectory should be  
854 explained, in particular to make explicit whether it is based on a statistical approach to reduce the dimension-  
855 ality of the exploration or on habits that are the result of clinical experience and interpretability of the chosen  
856 variables. Furthermore, the exact definitions of the variables used should be detailed and it should be precised  
857 if these variables depend strongly on the standardization of foot placement or on the length of the recording.  
858 In addition, despite the similarities that we observed between the values obtained with two different protocols  
859 of quiet stance balance recorded on two different samples of elderly people, it is advisable to follow when  
860 possible the recommendations concerning recording times (of at least 60s with several repetitions) and the  
861 sampling frequency (100 Hz and a cut-off frequency of 10 Hz) and a standardisation of the placement of the  
862 feet on the force platform (especially if the variables that depend on the base of support are used) Regarding the

863 instructions, the positioning of the arms, generally alongside the body, the use of instructions to the participant  
864 such as to remain stable without moving or the addition of a visual target to facilitate standing at a distance  
865 of a few meters from the person should be indicated. These recommendations must take into account the  
866 feasibility of recording balance in a real environment, which does not necessarily permit this level of standard-  
867 isation depending on the equipment used, the space available or the physical capacities of the elderly people  
868 being recorded, especially when their frailty leads to a high risk of falling, since these people are probably the  
869 ones who could benefit most from fine balance measurements. Future studies with a larger sample size and  
870 longitudinal follow-up could further investigate the choice of a combination of postural variables, as well as  
871 the benefits of multidimensional analysis in elderly people.

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