

# A review of center of pressure (COP) variables to quantify standing balance in elderly people: Algorithms and open-access code

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#### A Review of Center of Pressure (COP) Variables to Quantify 1 Standing Balance in Elderly People: Algorithms and Open 2 Access Code 3 Flavien Quijoux<sup>1, 2</sup>, Alice Nicolaï<sup>1</sup>, Ikram Chairi<sup>1,3</sup>, Ioannis Bargiotas<sup>1</sup>, Damien Ricard<sup>1, 4, 5</sup>, Alain Yelnik<sup>1,6</sup>, Laurent Oudre<sup>1</sup>, François Bertin-Hugault<sup>2</sup>, Pierre Paul 5 Vidal<sup>7, 1</sup>, Nicolas Vayatis<sup>1</sup>, Stéphane Buffat<sup>8</sup>, and Julien Audiffren<sup>9</sup> <sup>1</sup>Centre Borelli UMR 9010/Université Paris-Saclay, ENS Paris-Saclay, CNRS, SSA, 7 Inserm, Université de Paris, Paris, France 8 <sup>2</sup>ORPEA Group, Puteaux, France 9 <sup>3</sup>Groupe MSDA, Université Mohammed VI Polytechnique, Benguerir, Maroc 10 <sup>4</sup>Service de Neurologie de l'Hôpital d'Instruction des Armées de Percy, SSA, Clamart, 11 France 12 <sup>5</sup>Ecole du Val-de-Grâce, Ecole de Santé des Armées, Paris, France 13 <sup>6</sup>PRM Department, GH Lariboisière F. Widal, AP-HP, Université de Paris, UMR 8257, 14 Paris, France 15 <sup>7</sup>Institute of Information and Control, Hangzhou Dianzi University, Zhejiang, 310018, 16 China 17 <sup>8</sup>Laboratoire d'accidentologie de biomécanique et du comportement des conducteurs, GIE 18 Psa Renault Groupes, Nanterre, France 19 <sup>9</sup>Department of Neuroscience, University of Fribourg, Fribourg, Switzerland 20 Abstract 21

Postural control is often quantified by recording the trajectory of the center of pressure (COP) - also 22 called stabilogram - during human quiet standing. This quantification has many important applications, such 23 as the early detection of balance degradation to prevent falls, a crucial task whose relevance increases with 24 the ageing of the population. Due to the complexity of the quantification process, the analyses of sway pat-25 terns have been performed empirically using a number of variables, such as ellipse confidence area or mean 26 velocity. This study reviews and compares a wide range of state-of-the-art variables that are used to assess 27 the risk of fall in elderly from a stabilogram. When appropriate, we discuss the hypothesis and mathematical 28 assumptions that underlie these variables, and we propose a reproducible method to compute each of them. 29 Additionally, we provide a statistical description of their behavior on two datasets recorded in two elderly 30 populations and with different protocols, to hint at typical values of these variables. First, the balance of 133 31 elderly individuals, including 32 fallers, was measured on a relatively inexpensive, portable force platform 32 (Wii Balance Board, Nintendo) with a 25-seconds open-eyes protocol. Secondly, the recordings of 76 el-33 derly individuals, from an open access database commonly used to test static balance analyses, were used to 34 compute the values of the variables on 60-seconds, eyes-open recordings with a research laboratory standard 35 force platform. 36

#### Keywords 37

Postural Control, Quiet Standing, Center of Pressure, Elderly. 38

#### Correspondence 39

Flavien Quijoux, E-mail: f.quijoux@orpea.fr Location : 12 Rue Jean Jaurès, 92800 Puteaux, France. Medical 40

Direction, ORPEA 41

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## 47 **1** Introduction

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

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

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

the literature, some of them include several algorithmic steps which may not be convenient to code in the con-

text of clinical practice [Collins and De Luca, 1993, Chiari et al., 2000], highlighting the need of developing
 open-access codes to compute the variables. The aforementioned drawbacks make it particularly delicate to

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<sup>98</sup> compare the results of different studies and generalize their finding.

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

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

### 128 **2** Method

#### 129 **2.1** Literature review

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

The keywords were selected following the P.I.C.O framework to produce research equations such as "[OLDER ADULTS] + [QUIET STANDING] + FALL\* + DIFFERENC\*" (the exhaustive list is published in the protocol). The following MeSH terms were also used: "Accidental Falls/prevention & control", "Accidental Falls/statistics & numerical data\*", "Aged", "Postural Balance/physiology\*", "Posture/physiology\*",
 "Predictive Value of Tests" and "Regression Analysis". The general design was in accordance with PRISMA

and MOOSE guidelines. We refer the reader to PROSPERO database (CRD42018098671) and the published

<sup>150</sup> protocol [Quijoux et al., 2019] for more details.

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

### **160 2.2** Selection of COP variables

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

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

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

### **2.3** Corpus of the selected variables

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

• Positional variables

Variables that describe characteristics of the dispersion of the trajectory or position of the feet, and do
 not require the knowledge of the dynamics of the signal.

- Dynamic variables
- Variables based on the dynamic of the COP, requiring the knowledge of its local displacements.
- Frequency variables
- <sup>184</sup> Variables used to describe the Power Spectral Density of the COP trajectory.
- Stochastic variables
- Variables derived from the models in which the COP is represented as a stochastic process.

A more detailed description of each group is provided at the beginning of its respective part, in Section 3. It is important to note that these categories are not necessarily orthogonal, in the sense that features inside different groups could possibly be correlated. The classification inside distinct groups is nevertheless useful as these features rely on different models or mathematical concepts and therefore lead to interpretations of different nature. For instance, some stochastic features which are linked to diffusion phenomena could be positively correlated to positional features that also measure dispersion aspects of the signal, however in the first case the computation of the feature relies on a model of stochastic diffusion whereas in the second case the dynamic of
 the trajectory is not taken into account, leading to different interpretations.

#### 195 2.4 Data collection

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

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

**Experimental procedure** During these consultations, and before the experiment, patients were asked about 203 their history of falls in the last six months. Measurement of the COP displacement characteristics of the in-204 dividuals were then performed using a Wii Balance Board (WBB) (Nintendo, Tokyo, Japan), an alternative 205 to laboratory grade force platform that have received increased attention in the recent years for quantifying 206 postural control [Park and Lee, 2014, Severini et al., 2017]. The use of the WBB is justified by its advan-207 tages in terms of convenience compared to laboratory force platforms. Its within-device and between-device 208 reliability have been considered good and suitable for clinical settings [Clark et al., 2010], especially when preprocessing methods are applied to improve accuracy [Leach et al., 2014, Audiffren and Contal, 2016]. During 210 the static balance recording, patients were invited to stand on the platform. Data was collected by a custom 211 software on a Samsung tablet (Android operating system version 2.0, Samsung, Seoul, Korea), using Bluetooth 212 L2CAP protocol. The balance test was performed twice with different conditions. First, the individuals stood 213 in quiet stance, eyes open, looking straight ahead, arms at their sides and feet comfortably positioned within 214 the space provided on the WBB. After 10 seconds in this position, the trajectory of the COP was recorded 215 for 25 seconds, a duration that has been shown to be sufficient to quantify postural control with variables 216 [Bargiotas et al., 2018]. Then the individuals were asked to close their eyes. After a further 10 seconds, the 21 closed-eye recording was started for 25 seconds. Between the two phases, there was no rest period, except in 218 case of vertigo expressed by the subject. For the calculation of the variables, only the open eyes record is kept 219 (a single repetition). 220

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

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

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

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

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

Table 1: Characteristics of study participants

#### **252 2.5 Descriptive analysis**

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

#### 261 2.6 Open-access code

A code enabling the calculation of all the COP variables that are presented is available at 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<sub>s</sub> denotes the total duration of the signal in seconds. For each  $1 \le n \le N$ ,  $ML_n$  (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  $1 \le n \le N$ ,

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

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  $(R_n)_{1 \le n \le N}$  as the euclidean distance of the centered COP to the origin: for each

## $1\leq n\leq {\rm N},$

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

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

$$\operatorname{cov} = \frac{1}{N} \sum_{n=1}^{N} X_n Y_n$$

Symbol	Name	Formula	Units	Section
Т	Total duration of the signal	-	8	
Ν	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	$ML_n - \frac{1}{N}\sum_{i=1}ML_i$	cm	
$Y_n$	Centered AP Coordinates	$AP_n - \frac{1}{N}\sum_{i=1}AP_i$	cm	3.1
$R_n$	Radius	$\sqrt{X_n^2 + Y_n^2}$	cm	5.1
COV	Covariance AP ML	$\frac{1}{N}\sum_{n}X_{n}Y_{n}$	$\mathrm{cm}^2$	
$\mathrm{SD}_n$	Sway Density	see Def. 1	S	
$z_\ell$	Zero Crossing	see Def. 3	-	
$p_\ell$	Peaks	see Def. 4 and 2	-	33
$V_n^x$	ML Velocity	see Computing velocity and Notation	$\mathrm{cm.s}^{-1}$	5.5
$V_n^y$	AP Velocity	see Computing velocity and Notation	$\mathrm{cm.s^{-1}}$	
$V_n$	Velocity norm	$\sqrt{(V_n^x)^2 + (V_n^y)^2}$	$\mathrm{cm.s^{-1}}$	
$\Gamma_k^S$	PSD of S for frequency $kF_s/N$	-	$cm^2.Hz^{-1}$	2.4
$M_\ell^S$	$\ell\text{-th}$ Spectral Moment of $S$	$\sum_k f_k^\ell  \Gamma_k^S$	$\mathrm{cm}^2.\mathrm{Hz}^{\ell-1}$	3.4
$\mathrm{MSD}^S(\Delta t)$	Mean Square Deplacement of $S$	$\frac{\sum_{n} (S_{n+F_s\Delta t} - S_n)^2}{N - F_s\Delta t}$	$\mathrm{cm}^2$	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.

- 275 MEAN ML  $\frac{1}{N} \sum_{n=1}^{N} ML_n$
- 276 MEAN AP  $\frac{1}{N}\sum_{n=1}^{N}AP_n$

Feature	Full Name	Formula	Units
MEAN ML	Mean ML Coordinate	$\frac{1}{N}\sum_{n}ML_{n}$	cm
MEAN DIST. ML	Mean Distance ML	$rac{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	$\sqrt{\frac{1}{\mathrm{N}}\sum_{n}R_{n}^{2}}$	cm
RANGE ML	Amplitude ML	$\max_{n,m}  X_n - X_m $	cm
RANGE ML-AP	Amplitude ML-AP	$\max_{1 \le n \le m \le N} \sqrt{(X_n - X_m)^2 + (Y_n - Y_m)^2}$	cm
RANGE RATIO	Ratio of amplitudes	RANGE ML RANGE AP	-
PLANAR DEV.	Planar Deviation	$\sqrt{\mathrm{RMS}~\mathrm{ML}^2 + \mathrm{RMS}~\mathrm{AP}^2}$	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.	$\mathrm{cm}^2$
PRINCIPAL SWAY DIR.	Principal Sway Direction	$\arccos\left(\frac{ v_2 }{\sqrt{v_1^2 + v_2^2}}\right) \times \frac{180}{\pi}$	0

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,  $^{\circ}$  for degree (angle), and – for unitless.

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

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

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

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

- 293 MAX ML  $\max_{1 \le n \le N} |X_n|$
- 294 MAX AP  $\max_{1 \le n \le N} |Y_n|$
- 295 MAX RADIUS  $\max_{1 \le n \le N} R_n$

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

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

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

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

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

- 315 RANGE ML  $\max_{1 \le n \le m \le N} |X_n X_m|$
- 316 RANGE AP  $\max_{1 \le n \le m \le N} |Y_n Y_m|$
- 317 RANGE AP-ML  $\max_{1 \le n \le m \le N} \sqrt{(X_n X_m)^2 + (Y_n Y_m)^2}$

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

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\begin{array}{c} {}_{324} \quad \text{RANGE RATIO} \qquad \qquad \frac{\text{RANGE-ML}}{\text{RANGE-AP}} \end{array}
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Planar Deviation The planar deviation was defined by [Raymakers et al., 2005] as the square root of the sum of the variances of displacements in ML and AP directions. While it has been argued that this variable may be less discriminant than the range or the mean velocity [Raymakers et al., 2005] and has shown a small relative reliability, with an intraclass correlation coefficient (ICC) of 0.5, in eyes open condition, and a poor absolute reliability [Qiu and Xiong, 2015], the planar deviation has been used in multiple previous works to quantify human stability [Xiong and Karim, 2013, Ilett et al., 2016].

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

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

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



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

95% Confidence Ellipse Area (Sway Area) The confidence ellipse area (or sway area) is not always com-337 puted with the same definition and method in stabilometry studies [Schubert and Kirchner, 2014] Two main 338 definitions area used. One of the definitions used is related to the mathematical definition of an confidence 339 ellipse area, which is the area of the ellipse that contains the true mean of the signal with a high probability, 340 and the other is related to the mathematical definition of a prediction ellipse area, which is the area of the el-34 lipse that would contain a future observation with high probability [Schubert and Kirchner, 2014]. One major 342 drawback with the first definition and that it depends strongly on sample size. In this review, we propose to 343 use the prediction ellipse area definition, which show marginal variations with change in sample size [Schu-344 bert and Kirchner, 2014]. An increase of this feature value among elderly people has been associated with a significantly higher risk of fall [Merlo et al., 2012]. The feature is derived from using the central limit theorem 346 [Schubert and Kirchner, 2014, Prieto et al., 1996, Duarte and Freitas, 2010], which requires the assumption 347 that the serie samples are independent and identically distributed. Let  $F_{0.95,2,n-2}$  denote the 0.95-quantile of 348 the Fisher distribution with 2 and n-2 degrees of freedom. Note that the unbiaised versions of the covariance 349 matrix could also be used [Schubert and Kirchner, 2014]. The feature can be approximated by the following 350 formula 351

352 95 % conf. Area 
$$2\pi \times \frac{(N-1)(N+1)}{(N-2)N} \times F_{0.95,2,N-2} \times \sqrt{\text{RMS ML}^2 \times \text{RMS AP}^2 - \text{Cov}^2}$$

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

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

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

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

#### **364 3.3 Dynamic variables**

362

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



Feature	Full Name	Formula	Units
SWAY LENGTH ML	Sway Length ML	$\sum  X_{n+1} - X_n $	cm
		n	
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 $ML/T$	$\mathrm{cm.s}^{-1}$
MEAN SPD	Average Velocity	SWAY LENGTH/T	$\mathrm{cm.s}^{-1}$
AREA PER SEC.	Sway Area per sec.	$\frac{1}{2T}\sum_{n} X_{n+1}Y_n - X_nY_{n+1} $	$\mathrm{cm}^2.\mathrm{s}^{-1}$
STD SPD ML.	Deviation Velocity ML	$\sqrt{\frac{1}{\mathrm{N}}\sum_n (\mathrm{V}_n^x - \overline{\mathrm{V}^x})^2}$	${\rm cm.s^{-1}}$
STD SPD.	Deviation Velocity	$\sqrt{rac{1}{\mathrm{N}}\sum_n(\mathrm{V}_n-\overline{\mathrm{V}})^2}$	${\rm cm.s^{-1}}$
PHASE PLANE ML	ML Phase Plane Parameter	$\sqrt{\mathrm{rms}\ \mathrm{ml}^2 + \mathrm{std}\ \mathrm{spd}\ \mathrm{ml}^2}$	*
VFY	-	STD SPD <sup>2</sup> /MEAN AP	$\mathrm{cm.s}^{-2}$
LFS	Length over Area	SWAY LENGTH 95% CONF. AREA	$\mathrm{cm}^{-1}$
FRACTAL DIM	Fractal Dimension	see Def. Fractal Dimension	-
SET OF ZERO CROSS. ML	Set of Zero Crossings ML	$\mathcal{Z}^{\mathrm{V}^x}$	-
ZERO CROSS. ML	Number of Zero Crossings ML	$\# \mathcal{Z}^{\mathbf{V}^x}$	-
PEAK VEL. + ML	Mean Positive Peak of ML Vel.	see Def.	${\rm cm.s^{-1}}$
PEAK VEL ML	Mean Negative Peak of ML Vel.	see Def.	${\rm cm.s^{-1}}$
PEAK VEL. ML	Mean Peak of ML Velocity	$rac{1}{\mathrm{K}}\sum_\ell p_\ell^{\mathrm{V}^x}$	$\mathrm{cm.s^{-1}}$
PEAK SD	Mean Peak of Sway Density	$rac{1}{K}\sum_\ell p_\ell^{\mathrm{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	$rac{1}{4\sqrt{2}} imes rac{ ext{mean spd}}{ ext{mean dist}}$	Hz

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

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

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

373 where

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

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

<sup>379</sup> An example of peaks identified on a sway density signal is shown in Figure 3b.

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

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

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

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



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

<sup>390</sup> **Definition 3** (Zero crossing points of velocity).

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

393 1. For all 
$$\ell \in \{1, ..., J\}, V_{z_{\ell}-1} \times V_{z_{\ell}} \leq 0 \text{ and } V_{z_{\ell}} \neq 0$$

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

<sup>395</sup> **Definition 4** (Peaks of velocity).

Let  $V = (V_n)_{1 \le n \le N}$  stand for  $V^x$  or  $V^y$ . Let  $z_1, \ldots, z_J$  be the zero crossing points of V. Then for all  $1 \le \ell \le K = J - 1$ , the  $\ell$ -th peak of V occurs at the sampling variable  $n_{p_\ell^V}$  and is equal to  $p_\ell^V$ , where  $n_{p_\ell^V} = \log \max_{n \in \{1,\ldots,N\}}, z_{\ell} \le n \le z_{\ell+1} - 1$   $|V_n|$  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 400 widely used variables. Overall, the mean velocity is considered as one of the most reliable feature, especially 401 in the AP direction [Low et al., 2017]. This variable has been shown to be influenced by age-related postural 402 alterations, under both eyes-open and eyes-closed conditions [Prieto et al., 1993, 1996] and to be predictive 403 of the risk of falling [Howcroft et al., 2017]. Indeed, the COP movement velocity was significantly correlated 404 to age-related neuromuscular phenomena such as loss of plantar flexor muscle volume [Kouzaki and Masani, 405 2012], tremors [Kouzaki and Masani, 2012] or an increase of the co-contraction strategy of agonist and antag-406 onist muscles of the leg [Benjuya et al., 2004, Carpenter et al., 2001a, Ho and Bendrups, 2002, Nelson-Wong 407 et al., 2012]. The perception of the COP movement velocity could be an important factor in the control of ankle 408 extensor activity through anticipatory strategies [Masani, 2003, Sun et al., 2019], highlighting the impact of 409 age-related neuromuscular deterioration on static balance, with significant differences between eyes open or 410 closed conditions [Howcroft et al., 2015] and more generally on the risk of falling [Brauer et al., 2000, Kwok 411 et al., 2015]. For a constant sampling interval, the mean velocity is defined as the sum of the distances between 412 consecutive points, also called sway length, divided by the duration of the recording. Therefore, the mean ve-413 locity can be seen as a normalized version, with respect to the duration, of the sway length, which has been 414 previously cited as the most common feature in the literature to evaluate the effect of exercise interventions 415 [Low et al., 2017], and has been shown to distinguish people at risk of falling from healthy people [Kantner 416 et al., 1991]. 417

418
 SWAY LENGTH ML
 
$$\sum_{n=1}^{N-1} |X_{n+1} - X_n|$$

 419
 SWAY LENGTH AP
  $\sum_{n=1}^{N-1} |Y_{n+1} - Y_n|$ 

 420
 SWAY LENGTH
  $\sum_{n=1}^{N-1} \sqrt{(X_{n+1} - X_n)^2 + (Y_{n+1} - Y_n)^2}$ 

n=1



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.

	MEAN ODD MI	SWAY LENGTH ML
421	MEAN SPD ML	Т
422	MEAN SPD AP	$\frac{\text{SWAY LENGTH AP}}{\text{T}}$
423	MEAN SPD	$\frac{\text{SWAY LENGTH}}{\text{T}}$

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

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

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

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

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

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

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

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

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

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

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

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.

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

476 FRACTAL DIM 
$$\frac{\log N}{\log N + \log \sqrt{\frac{4}{\pi} \times 95\% \text{ conf. Area}} - \log \text{Sway length}}$$

Zero Crossing (of Velocity) This variable is defined as the number of times that the COP velocity crosses 477 the zero value axe [Jeong et al., 2007]. Tuunainen et al. indicated that "zero crossing velocity showed a high 478 rate of velocity change around the neutral position of stance" [Tuunainen et al., 2013]. The latter found an 479 association between this variable and falls, but no significant difference between fallers and non-fallers, which 480 is in line with previous results that found no significant difference, even when comparing the two groups of 48 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 482  $V^x$ , respectively  $V^y$ , given by Definition 3. The zero crossing variables represent the number of zero crossing 483 points in each direction: 484

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

486 ZERO CROSS. AP  $\# \mathcal{Z}^{V^{\mathcal{Y}}}$ 

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

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

 $\begin{array}{l} {}_{497} \quad \text{PEAK AP VEL. + ML} \qquad \qquad \frac{\sum_{\ell=1}^{K} p_{\ell}^{\text{V}^{x}} \times 1\!\!1_{\left\{p_{\ell}^{\text{V}^{x}} > 0\right\}}}{\sum_{\ell=1}^{K} 1\!\!1_{\left\{p_{\ell}^{\text{V}^{x}} > 0\right\}}} \\ {}_{498} \quad \text{PEAK AP VEL. - ML} \qquad \qquad \frac{\sum_{\ell=1}^{K} p_{\ell}^{\text{V}^{x}} \times 1\!\!1_{\left\{p_{\ell}^{\text{V}^{x}} < 0\right\}}}{\sum_{\ell=1}^{K} 1\!\!1_{\left\{p_{\ell}^{\text{V}^{x}} < 0\right\}}} \\ {}_{499} \quad \text{PEAK AP VEL. ML} \qquad \qquad \frac{1}{K} \sum_{\ell=1}^{K} p_{\ell}^{\text{V}^{x}} \end{array}$ 

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

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

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

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

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

*Mean Frequency* The mean frequency is defined by [Prieto et al., 1996] as the rotational frequency, considering the total length of the COP as a trajectory around a circle with a radius equals to the mean distance. This variable is proportional to the ratio of the mean velocity to the mean distance, which has been studied in [Hufschmidt et al., 1980]. In [Maki et al., 1994], the mean frequency does not significantly differ between fallers and non-fallers in prospective follow-up. This result is in line with other studies on then retrospective evaluation of falls [König et al., 2014, Maranesi et al., 2016]. However, it has been argued that MEAN FREQUENCY, especially in the AP direction, can be used to distinguishing elderly fallers from non-fallers [McGrath et al., 2012], and is reliable [Qiu and Xiong, 2015].

529	MEAN FREQ. ML	$\frac{1}{4\sqrt{2}}\times\frac{\text{mean SPD ml}}{\text{mean dist ml}}$
530	MEAN FREQ. AP	$\frac{1}{4\sqrt{2}}\times\frac{\text{mean SPD AP}}{\text{mean dist AP}}$
531	MEAN FREQ. ML-AP	$\frac{1}{2\pi} \times \frac{\text{mean SPD}}{\text{mean Dist}}$

### 532 3.4 Frequency variables

Feature	Full Name	Formula	
TOTAL POWER ML	Total Power ML	$\sum_{k=k_{ ext{inf}}}^{k_{ ext{sup}}} \Gamma_k^X$	$\mathrm{cm}^2$
50 % power freq ml	Median of PSD ML	$\inf\left\{k^{\star} \in \mathbb{N}, \ \sum_{k=k_{\inf}}^{k^{\star}} \Gamma_k^X \ge 0.5 \sum_{k=k_{\inf}}^{k_{\sup}} \Gamma_k^X\right\} \times \frac{\mathbf{F}_s}{\mathbf{N}}$	Hz
95 % power freq ml	95% percentile of PSD ML	$\inf \left\{ k^{\star} \in \mathbb{N}, \sum_{k=k_{\inf}}^{k^{\star}} \Gamma_k^X \ge 0.95 \sum_{k=k_{\inf}}^{k_{\sup}} \Gamma_k^X \right\} \times \frac{\mathbf{F}_s}{\mathbf{N}}$	Hz
POWER MODE ML	Mode of PSD	$rac{\mathrm{F}_s}{\mathrm{N}}  imes rg\max_{k_{\mathrm{inf}} \leq k \leq k_{\mathrm{sup}}} \Gamma_k^X$	Hz
CENTROIDAL FREQ ML	Centroidal Frequency ML	$\sqrt{rac{M_2^X}{M_0^X}}$	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	$\sum_{k \in \mathcal{A} \in \mathcal{A}} \Gamma^X(f_k)$	$\mathrm{cm}^2$
energy 0.5-2 hz ml	Energy Content 0.5-2Hz ML	$\sum_{\substack{0.5 < f_k \leq 0.5}} \Gamma^X(f_k)$	$\mathrm{cm}^2$
energy $> 2$ Hz ml	Energy Content above 2Hz ML	$\sum_{2 < f_k \leq f_{\sup}}^{0.5 < f_k \geq 2} \Gamma^X(f_k)$	$\mathrm{cm}^2$
FREQ. QUOTIENT ML	Frequency Quotient	$\frac{\sum_{2 < f_k \le 5} \Gamma^X(f_k)}{\sum_{f_{\inf} < f_k \le 2} \Gamma^X(f_k)}$	-

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.

This category is similar to the one presented in [Prieto et al., 1996], and includes the variables used to describe the Power Spectral Density of the COP trajectory. Similarly to the dynamic variables, these descriptors 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  $f_{inf} = 0.15 H_z$  to  $f_{sup} = 5 H_z$ , which corresponds to variables  $k_{inf} = \lfloor 0.15 \frac{N}{F_s} \rfloor + 1$  and  $k_{sup} = \lfloor 5 \frac{N}{F_s} \rfloor$ , an interval likely to provide significant information about the postural control system [Prieto et al., 1996]. We denote by

$$M^X_\ell = \sum_{k=k_{\rm inf}}^{k_{\rm sup}} f^\ell_k \, \Gamma^X_k$$

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

<sup>537</sup> Welch's method with 10 seconds segments, with 50% overlapping and linear detrending [Vieira et al., 2009a].

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

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

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

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

550 50% power freq. ML 
$$\inf \left\{ k^{\star} \in \mathbb{N}, \ \sum_{k=k_{\inf}}^{k^{\star}} \Gamma_k^X \ge 0.5 \sum_{k=k_{\inf}}^{k_{\sup}} \Gamma_k^X \right\} \times \frac{F_s}{N}$$

551 95% Power freq. ML 
$$\inf \left\{ k^{\star} \in \mathbb{N}, \sum_{k=k_{\inf}}^{k^{\star}} \Gamma_k^X \ge 0.95 \sum_{k=k_{\inf}}^{k_{\sup}} \Gamma_k^X \right\} \times \frac{F_s}{N}$$

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

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

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

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

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

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

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	$\exp(\hat{lpha}_s^X)$
LONG-TERM DIFF. ML	Long term diffusion coefficient ML	$\exp(\hat{lpha}_\ell^X)$
SHORT-TERM SCAL. ML	Short term Scaling coefficient ML	$\hat{\beta}_s^X/2$
LONG-TERM SCAL. ML	Long term Scaling coefficient ML	$\hat{eta}_\ell^X/2$
CRIT. TIME ML	Critical Time ML	$\exp\left(rac{\hat{eta}_s^X - \hat{eta}_\ell^X}{\hat{lpha}_s^X - \hat{lpha}_\ell^X} ight)$
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.

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

581 ENERGY 
$$\leq 0.5$$
 HZ 
$$\sum_{f_{inf} < f_k \leq 0.5} \Gamma^X(f_k)$$
  
582 ENERGY 0.5-2 HZ 
$$\sum_{0.5 < f_k \leq 2} \Gamma^X(f_k)$$

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

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

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

#### 586 3.5 Stochastic variables

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

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

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

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

<sup>592</sup> 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.

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

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

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 long-term diffusion coefficients. Note that the model and the computation technique proposed in [Chiari et al., 2000] are not exactly the same as the one formerly introduced in [Collins and De Luca, 1993], therefore the resulting features are not directly comparable with the previous ones. However the general interpretation of the variables remains similar. <sup>617</sup> *Diffusion and scaling coefficients* For parameters estimation, the two regimes (short-term and long-term) of <sup>618</sup> the MSD are approximated by two linear functions of the time interval on a logarithmic scale:

If this model fitted perfectly the data, we could directly search for the time  $\Delta t_c$  which separates the diffusion 619 plot into two different linear regions. However, as stated in [Chiari et al., 2000], there exists for some tra-620 jectories a transition region in the MSD curve which is not well fitted by a linear model. For this reason the 62 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 622 [0.3s, 2.5s] as the highest time stamp which minimizes the root mean square error (RMSE) in the Ordinary 623 Least Square (OLS) fit of the model (1), then the long-term regime is estimated on a second region  $[\Delta t_2, \Delta t_N]$ 624 where  $\Delta t_{\rm N} = T/3$  and  $\Delta t_2$  is defined in the range [0.3s, 2.5s] as the highest time stamp which minimizes 625 the mean square error in the Ordinary Least Square (OLS) fit of the model (2). An illustration of this estima-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  $\beta_\ell^X$ , 626 627 respectively. Then: 628

- 629 SHORT-TERM DIFF. ML  $\exp(\hat{\alpha}_s^X)$
- 630 LONG-TERM DIFF. ML  $\exp(\hat{lpha}_\ell^X)$
- 631 SHORT-TERM SCAL. ML  $\frac{\hat{eta}_s^X}{2}$
- 632 LONG-TERM SCAL. ML  $\frac{\hat{\beta}_{\ell}^X}{2}$

<sup>633</sup> These indices are similarly defined for the AP axis through replacing X by Y.

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

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

655 CRIT. TIME ML

$$\operatorname{p}\left(\frac{\hat{\beta}_s^X - \hat{\beta}_\ell^X}{\hat{\alpha}_s^X - \hat{\alpha}_\ell^X}\right)$$

ex

Note that if the estimated critical time is larger than duration limit  $\Delta t_{\rm N}$ , it is set at  $\Delta t_{\rm N}$ . The critical mean square displacement is defined as

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

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

#### **3.6 Descriptive analysis**

Average values of the different variables, and their standard deviations, are reported in Table 7. Vari-661 ables that are strongly correlated to the total duration of the recording (such as LFS ML AND AP) are reported 662 separaterly in the second part of the table. Interestingly, and despite the signifiant differences between the 663 two datasets, the range of values obtained for were comparable for most variables. However, there are 664 still some noticeable differences, particularly for the variables PEAK VELOCITY ML, TOTAL POWER ML, 665 ENERGY CONTENT BELOW 0.5HZ ML and SHORT TIME DIFFUSION ML which show standard deviations 666 higher than the means on the SmartCheck database. This is in line with previous works that have hypoth-667 esized that longer recording duration might be necessary for the proper evaluation of the power spectrum 668 [Vieira et al., 2009b]. Moreover, the standard deviation of the variables is generally higher in the recordings 669 from our protocol, which might result from both the shorter recording duration, and the more varied demo-670 graphics. 67

### 672 **4 Discussion**

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

#### **4.1** Ageing and postural control

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

In the recent years, numerous methods have been proposed to analyse the trajectory of the COP, in order to investigate the differences between elderly fallers and non-fallers, as presented in our previous systematic review [Quijoux et al., 2020]. At the same time, the univariate analysis of postural variables provides limited information on the physiological causes of falls [Duarte and Freitas, 2010]. This has encouraged 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	$1.89 \pm 1.00$ 2.05 $\pm$ 1.16	$1.47 \pm 0.65$ 1.58 $\pm$ 0.68
rms MI	$2.05 \pm 1.10$ 0.40 ± 0.31	$1.38 \pm 0.08$ 0.30 ± 0.12
rms AP	$0.40 \pm 0.31$ $0.66 \pm 0.35$	$0.30 \pm 0.12$ $0.49 \pm 0.24$
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	$0.83 \pm 0.68$ 1.60 $\pm$ 1.26	$0.50 \pm 0.22$
mean velocity ML AND AP	$1.00 \pm 1.30$ $1.07 \pm 1.60$	$0.87 \pm 0.39$ 1 10 ± 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	$0.56 \pm 0.29$	$0.42 \pm 0.15$
total power MI	$0.48 \pm 0.22$ 3 03 + 8 22	$0.37 \pm 0.12$ 2 14 + 2 08
total power AP	$6.33 \pm 8.52$	$5.66 \pm 10.22$
power frequency 50 ML	$0.33 \pm 0.02$ $0.42 \pm 0.13$	$0.00 \pm 10.22$ $0.43 \pm 0.14$
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	$1.33 \pm 0.56$	$1.23\pm0.24$
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	$2.23 \pm 7.21$	$1.30 \pm 1.75$ 2.67 $\pm$ 9.47
energy content 05.2 MI	$4.23 \pm 5.71$ 0.75 $\pm$ 1.97	$3.07 \pm 0.47$ 0.76 ± 0.90
energy content 05 2 ML	$0.73 \pm 1.27$ 1 83 + 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	$0.08 \pm 0.47$ 0.81 $\pm$ 1.17	$0.43 \pm 0.24$ 0.22 $\pm$ 0.58
short time scaling AP	$0.01 \pm 1.17$ 0.81 $\pm$ 0.10	$0.22 \pm 0.38$ 0.88 ± 0.02
long time scaling AP	$0.81 \pm 0.10$ $0.08 \pm 0.18$	$0.88 \pm 0.03$ $0.18 \pm 0.12$
Duration sensitive variables	Mean $\pm$ std (WBB dataset)	Mean $\pm$ std (Public dataset)
	14.40 1 0 50	01 02 L 14 00
LES ML AND AP	$1/1/10 \pm 0.57$	31 76 + 1/1 83
LFS ML AND AP fractal dimension ML AND AP	$14.49 \pm 9.52$ 1.88 + 0.23	$31.26 \pm 14.83$ $1.98 \pm 0.15$
LFS ML AND AP fractal dimension ML AND AP zero crossing SPD ML	$14.49 \pm 9.52$ $1.88 \pm 0.23$ $127.43 \pm 34.16$	$31.26 \pm 14.83$ $1.98 \pm 0.15$ $195.47 \pm 32.94$

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-acces dataset of human balance [Santos and Duarte, 2016a]. Duration sensitive variables refer to variables that are strongly dependent on the duration of the recording.

in a particular axis and in two dimensions – to fully capture the COP dynamics and the age-related motor 704 adaptations [Bargiotas et al., 2018]. Indeed, age-related decline in postural control is not uniform, which is 705 understandable given the various anatomical structures that may be affected [Shaffer and Harrison, 2007]. 706 Distal myelin fibres and sensory receptors are affected by senescence and sedentary life, leading to im-70 paired proprioception, particularly in the hips, knees and ankles [Horak et al., 1989, Robbins et al., 1995], 708 as well as loss of touch discrimination [Perry, 2006], with a potential predominance in the distal joints of 709 the lower limb [Pickard et al., 2003, Shaffer and Harrison, 2007]. At the neuromuscular level, all the con-710 tractile properties of the muscles are impacted [Liu et al., 2005], notably by the reduction in the vascular 71 feeding system and thus, in the number of muscle fibres, their volume and their contractibility. Presynap-712 tic inhibition of Ia afferents, which plays a role in leg muscle contractility, is more favoured in the elderly 713 when sensory and somaesthetic afferents are reduced [Baudry and Duchateau, 2012]. This type of neuromus-714 cular alteration could partly explain the the adoption of a leg muscle co-contraction strategy in the elderly 715 [Papegaaij and Hortobágyi, 2017]. This co-contraction may reduce the exploitation of proprioceptive afferents 716 from the mechanoreceptors [Benjuya et al., 2004, Baudry, 2016, Craig et al., 2016] and the efficiency of the 717 muscular efferents in the segmental control of balance [Finley et al., 2012, Nelson-Wong et al., 2012]. A sig-718 719 nificant correlation between the increase in co-contraction measured in the elderly and the increase in MAX AP was found, whereas it was absent in young adults [Baudry and Duchateau, 2012]. As a result, studies agree 720 that an overall shift in balance control from spinal to supraspinal levels occurs in older adults, in line with 721 what is found in healthy subjects when proprioceptive afferents decrease [Alizadehsaravi et al., 2020]. Given 722 the diversity of disorders affecting the elderly, a bilateral alteration of the vestibular system could lead to an 723 increase in the values of the COP variables, as seen on SWAY LENGTH [Mbongo et al., 2005]. When visual 724 inputs are altered (with the use of a moving target), there is an increase in the contribution of the knee and hip 725 joints, which correlate with an increase in COP variables in the elderly people [Freitas and Duarte, 2012]. An 726 increase in the amplitude of displacement suggests a decrease in the ability to maintain a stable upright posi-727 tion, but the diversity of results obtained for positional and dynamic variables led Palmieri et al. to minimize 728 their clinical interpretation [Palmieri et al., 2002]. Dynamic, frequency and stochastic variables could pro-729 vide complementary and clinically relevant information. Although more studies are needed before concluding 730 on their physiological interpretation, we note that biomechanical modelling has shown a negative correlation 73 between the supposed stiffness of the system and mean frequency and MEAN VELOCITY, but positive with 732 CRITIAL TIME [Maurer and Peterka, 2005]. 733

#### 734 4.2 Feature classification

To the best of our knowledge, the classification of posturographic variables that is introduced in this study is 735 new and differs from previous classification paradigms. [Duarte and Freitas, 2010] used a classification which 736 distinguishes the descriptors resulting from a *structural analysis* -i.e. which aim to explain the control postu-737 ral commands through the behaviour of the COP, with sway density models or stochastic models - from other 738 variables. In [Prieto et al., 1996], four categories of descriptors were proposed: (1) Time-Domain Distance 739 measures, (2) Time-Domain Area measures, (3) Hybrid measures, and (4) Frequency-Domain measures. The 740 first class includes features associated with either the displacement of the COP from the average, or the veloc-74 ity; the second gathers geometric approximations of the surface of the COP; the third includes combinations 742 of distance measures [Prieto et al., 1996], which have been considered by others as dimensionless features 743 [Qiu and Xiong, 2015]; the fourth contains variables related to the analysis of the power spectral density of the 744 COP trajectory, usually obtained through Fast Fourier Transformation (FFT). Our classification, while similar 745 to the one proposed in [Prieto et al., 1996], presents two major differences. First, since the work of [Prieto 746 et al., 1996], popular stochastic models have been developed [Collins and De Luca, 1993, Duarte and Freitas, 747 2010, Qiu and Xiong, 2015]. Hence we introduce a fourth category of variables, called Stochastic descriptors, 748 which includes the features derived from stochastic based models of the COP. Second, we choose to regroup 749 the non-stochastic, non-frequency derived descriptors into positional and dynamic classes. Importantly, this 750 classification originated from signal processing concepts, and its main purpose was to ease the reading of this 75 study. 752

#### 753 4.3 Variables reliability

The reliability of stabilogram variables depends on several factors. The variation in the values of the posturographic variables recorded on the force platform reflect the participation of the muscles involved in maintaining balance and the contribution of the joints to postural oscillations. Feet placement could also <sup>757</sup> modify postural strategy in older population [Winter et al., 1996, Chiari et al., 2002]. For instance, when feet <sup>758</sup> are joined, the ML displacements of the COP are mostly influenced by the hip adductors and abductors, <sup>759</sup> whereas in the tandem position, movements in the ML direction are mostly related to the contractions of <sup>760</sup> the invert and spurs muscles of the leg [Winter et al., 1996, 2003, Prince et al., 1995]. In the upright, straight <sup>761</sup> position, feet open up by 45° apart, the movement in the ML direction is a mix of hip and ankle strategies, <sup>762</sup> whereas the AP displacements are under the dominance of the ankle muscles.

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

The differences between the values reported in the literature may also be explained by differences in equip-786 ment, sampling frequency, preprocessing and acquisition protocol [Carpenter et al., 2001b, Ruhe et al., 2010, 787 Vieira et al., 2009b, Schmid et al., 2002]. First, the sampling frequency varies greatly between studies. The 788 sampling frequency seems to have a greater impact on frequency variables than on positional and dynamic vari-780 ables. Rhea et al. add that a decrease in the sampling frequency (from 100 Hz to 25 Hz) has a non-significant impact on the non-linear analyses to obtain the stochastic variables [Rhea et al., 2015]. The reliability of the 791 WBB, used in this study, has been widely studied in the literature and the authors generally conclude that it 792 can be used to record balance [Clark et al., 2010, Bartlett et al., 2014, Abujaber et al., 2015, Severini et al., 793 2017]. However, we would emphasize the need to correct the sampling frequency of this force platform and 794 refer the readers to our previous work for more details [Audiffren and Contal, 2016]. 795

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

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

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

the parameters [Carroll and Freedman, 1993].

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

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

This review focuses on the variables used to discriminate between elderly fallers and other older adults. 819 However, in order to generalize the description of the variables, and more generally the mathematical require-820 ments for calculating them, it was necessary to extend the search to the references of the articles, which made 82 it possible to highlight the reliability of several indices as well as their variability according to age. This review 822 does not take into account indices that can be used to distinguish between younger and older participants and 823 as such cannot be described as comprehensive. Many other posturographic variables have been proposed to 824 assess the risk of falls in older people, either through measures of dynamic balance [Ringhof and Stein, 2018], 825 or in correlation with clinical assessments of motor skills [Karlsson and Frykberg, 2000, Cheng et al., 2012], 826 or because they are less commonly found in the literature, which did not fit the selection criteria of this review. 827 Regarding the latter, we have not included variables based on biomechanical or other equilibrium modelling 828 [McKee and Neale, 2019, Koltermann et al., 2020, Nicolai et al., 2021], as well as several other modelizations 829 such as wavelet analyses [Chagdes et al., 2009], sample entropy analysis and other associated entropies com-830 putations [Gow et al., 2015, Degani et al., 2017] or analyses based on markov chains [Hur et al., 2012]. To 831 overcome these limitations, further literature reviews should be conducted in the future to explore the most 832 recent methods that have been applied to the postural signals. This would require going beyond the variables 833 used to discriminate between fallers and non fallers. 834

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

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

## **5** Conclusion

A review of the literature on the analysis of the characteristics of the center of pressure for the discrim-846 ination of elderly people at high risk of falling revealed the lack of information concerning the methods of 847 calculation of the posturographic variables used, as well as the lack of homogeneity and standardization be-848 tween studies. By presenting a comprehensive glossary of calculation methods and a library of functions that 849 is as clear and exhaustive as possible, this should facilitate reproducibility between studies. Comparison with 850 future studies should also be made easier by providing a basis for comparing these variables for two different 851 protocol of COP recording, in elderly participants, with or without a history of falls. The choice of the selec-852 tion of variables among the growing number of possible methods of analysis of the COP trajectory should be 853 explained, in particular to make explicit whether it is based on a statistical approach to reduce the dimension-854 ality of the exploration or on habits that are the result of clinical experience and interpretability of the chosen 855 variables. Furthermore, the exact definitions of the variables used should be detailed and it should be precised 856 if these variables depend strongly on the standardization of foot placement or on the length of the recording. 857 In addition, despite the similarities that we observed between the values obtained with two different protocols 858 of quiet stance balance recorded on two different samples of elderly people, it is advisable to follow when 859 possible the recommendations concerning recording times (of at least 60s with several repetitions) and the 860 sampling frequency (100 Hz and a cut-off frequency of 10 Hz) and a standardisation of the placement of the 86 feet on the force platform (especially if the variables that depend on the base of support are used) Regarding the 862

instructions, the positioning of the arms, generally alongside the body, the use of instructions to the participant such as to remain stable without moving or the addition of a visual target to facilitate standing at a distance of a few meters from the person should be indicated. These recommendations must take into account the feasibility of recording balance in a real environment, which does not necessarily permit this level of standardisation depending on the equipment used, the space available or the physical capacities of the elderly people

being recorded, especially when their frailty leads to a high risk of falling, since these people are probably the

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

<sup>871</sup> the benefits of multidimensional analysis in elderly people.

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