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A Langevin-Based Model With Moving Posturographic Target to Quantify Postural Control

Alice Nicolai¹, Myrto Limnios, Alain Trouvé, and Julien Audiffren²

Abstract— Falls are a major concern of public health, particularly for older adults, as the consequences of falls include serious injuries and death. Therefore, the understanding and evaluation of postural control is considered key, as its deterioration is an important risk factor predisposing to falls. In this work we introduce a new Langevin-based model, local recall, that integrates the information from both the center of pressure (CoP) and the center of mass (CoM) trajectories, and compare its accuracy to a previously proposed model that only uses the CoP. Nine healthy young participants were studied under quiet bipedal standing conditions with eyes either open or closed, while standing on either a rigid surface or a foam. We show that the local recall model produces significantly more accurate prediction than its counterpart, regardless of the eyes and surface conditions, and we replicate these results using another publicly available human dataset. Additionally, we show that parameters estimated using the local recall model are correlated with the quality of postural control, providing a promising method to evaluate static balance. These results suggest that this approach might be interesting to further extend our understanding of the underlying mechanisms of postural control in quiet stance.

Index Terms— Center of mass (CoM), center of pressure (CoP), langevin model, postural control, stochastic dynamics.

I. INTRODUCTION

IN OUR ageing societies, falls are a major concern of public health [1]. This is especially true for older adults, as the consequences of falls are more severe, including serious injuries and death [2], and their prevalence is high, as each year more than a third of population 65 years-old and older faces a fall [3]. While strategies of prevention and rehabilitation have been shown to be effective to reduce those falls and their consequences [4], [5], they rely on an early detection and accurate characterization of the individual balance related deficiencies. In particular, the evaluation of postural control – the ability to maintain equilibrium and orientation in a gravitational environment [6] – is considered key to this end [7]

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as its deterioration is an important risk factor predisposing to falls [4].

Postural control results from the complex synergy between the central nervous system, the musculoskeletal system and the sensory entries (visual, somatosensory and vestibular) [8]–[11]. A common approach to evaluate postural control is to use protocols that inhibit visual (such as the Romberg test [12]) or proprioceptive feedbacks (using e.g. foam [13]) while recording the position of the center of pressure (CoP) – the point of application of the ground reaction forces resultant under the feet [14] – over time using a force platform. The recorded two-dimensional signal, which includes both the medio-lateral (ML) and antero-posterior (AP) axes, can be used to analyse the neuromuscular control involved, and in particular the adjustments performed by the individual to maintain balance, i.e. to keep the projection of the center of mass (CoM) inside the base of support [15], [16].

In previous works, multiple descriptors derived from the CoP have been shown to capture discriminatory characteristics of postural control [16]–[18]. More precisely, they were shown to present statistically significant different values among distinct populations such as older adults fallers, athletes, or individuals with neurological disorders such as Parkinson’s disease [19], [20]. Those descriptors can be general statistics of the signals, such as mean velocity or sway density [21], or parameters derived from dynamic models [11], [22], [23]. A significant benefit of the later approach is that it enables an interpretable parametrization of trajectories that arises directly from the formulation of the dynamic model.

Interestingly, several of these aforementioned models have assumed the presence of randomness in the CoP trajectory, due to either self-induced perturbations of postural control or external perturbations such as respiration [24], as well as the inaccuracy of the sensorimotor system. Consequently, these previous studies have proposed to model the CoP signal as a stochastic process [22], [25]. For instance, it has been suggested that the CoP displays a mean quadratic displacement similar to the one of a fractional brownian motion with two regimes [22]. Other works have proposed to model the CoP dynamic using Langevin differential equations [26]–[29]. This model has shown to be promising to reproduce intrinsic characteristics of the trajectory [26]. In this setting, the acceleration of the CoP is expressed as the combination of several of the following forces: a spring restoring

force, also called recall, a damping force and a Brownian motion.

Possible interpretations have been proposed for these forces. For instance, the recall force has been used to express the corrective force acting on the CoP to pull it back towards a reference position [23], [29].

This is in line with previous works that have advocated for the existence of a mechanism that produces a corrective ankle joint moment, which can be modeled as a spring restoring force, eventually damped [11], [15], [30]. Since the parameters of each force can be estimated using e.g. ordinary least-square method applied on transformations of the signal, such as the mean squared displacement [27], or directly on the CoP signal [26], it is possible to evaluate the relative importance of each force, hence giving insights about the characteristics of balance control. It has been claimed for instance that this model enables the evaluation of individual stiffness [29].

However, we argue that these Langevin-based models can be significantly improved by including the center of mass (CoM) as part of the system. Indeed, one popular hypothesis states that the CoM trajectory operates as a moving reference position, from which any deviation results in the activation of appropriate restoring forces [31], [32]. This assumption has been strengthened by previous studies which have shown that during quiet stance, the CoP oscillates in phase with the CoM with higher amplitudes [15]. Moreover, this hypothesis has been successfully applied to continuous linear feedback controllers with time delay system such as PID (Proportional, Integral, Derivative) systems to model the control of body deviations [11], [33], [34].

In line with these results, in the present study we introduce a new Langevin model that includes a recall force pulling the CoP toward the CoM, in addition to a damping force and a Brownian noise. Our experiments show that this model significantly improves the quality of the CoP trajectory predictions, compared to a commonly used Langevin model, including when subjects' vision and/or standing surface were manipulated. Additionally, we show that the same results can be obtained on another publicly available dataset of postural control [35]. We also used this new model to estimate the relative importance of each force, and our results show that these parameters can be used to differentiate between distinct populations and experimental conditions, highlighting their possible use to improve the understanding of several aspects of postural control. Overall, the present study supports the hypothesis that the CoP dynamic is intrinsically and deeply intertwined with the CoM dynamic, and that the Langevin model has the potential to quantify interesting components of postural control and can greatly benefit from encoding joint dynamic of the CoP and CoM instead of their marginal behavior.

II. METHOD

A. Participants and Protocol

In this study we analysed our model using two different populations. For the first population (hereafter referred to as population 1), 9 healthy young participants were recruited

specifically for this study (age: 27.6 ± 7.1 years, weight: 73.0 ± 6.5 kg, height: 170.0 ± 10.1 cm, three females). All participants were right-hand dominant with normal or corrected to normal vision. All participants signed an informed consent document approved the 22 July 2020 by the IRB of the Fribourg University, Switzerland, ref. 583R3.

Participants were asked to stand still with feet at pelvis width, arms laying at the side. For each acquisition, this quiet stance was recorded for 50 seconds, using a force platform and a kinematic system. Each participant was recorded twice for each possible combination of the following conditions: eyes open or closed, and standing on a surface that was either rigid or foam. During trials with eyes open, participants were asked to fix a target which was located at eyes height, at two meters distance. Trials were acquired in blocks of two consecutive recordings, in order to reduce confounding factors, such as fatigue or learning [23]. In between blocks, subjects were allowed to rest by sitting or walking around.

We replicated our results by using the public dataset [35] (hereafter referred to as population 2), which contains three-dimensional kinematics and the ground reaction forces of 49 subjects (27 young individuals – 15 males, 12 females – between 18 and 40 years old; 22 older adults – 11 males and 11 females – 60 years old or older). The database contains 588 recordings in total, among which 17 were removed as their kinematics time series were missing. All subjects were recorded in similar conditions as the first population, and both subjects' vision and the standing surface were identically manipulated.

B. Hardware

For our study, CoP data were collected using a ground-level six-channel force platform (AccuSway, AMTI, Watertown, MA, USA), which sampled the three-dimensional ground reaction forces and moments at 100 Hz. A poster was used to provide a 5-cm fixation target that was displayed approximately two meters in front of the participant, at eye level, during eyes open conditions. In order to standardise the shoe–platform interface, participants were recorded while wearing standardised socks. Kinematic data were collected using an OptiTrack system (NaturalPoint, Corvallis, OR, USA) at a sampling rate of 100 Hz using 18 cameras. Each participant wore a full body suit, on which markers were placed to track the position of key anatomical locations, which were used to compute the position and trajectory of the CoM during the recording. More specifically, markers were positioned following the model defined in [36], [37]. The detailed position of the markers can be found in Table I.

C. Data Preprocessing

Data from the force platform and the Optitrack system were collected and synchronised using Motive (NaturalPoint, Corvallis, OR, USA). Data preprocessing and analysis software were written using Python (v3.7, Python Software Foundation, OR, USA). Raw force platform data were processed with a fourth-order, zero-lag, low-pass Butterworth filter with a

TABLE I
MARKER POSITIONS USED FOR COM
TRACKING, SORTED BY BODY PART

Body part	Markers positions
Head	Vertex, Midpoints between gonions
Trunk	Acromions, Xyphoid, Antero-superior iliac splines
Arms	Acromions, Elbow joint centers, Styloid processes, and Distals of the tips of the third metacarpes
Legs	Greater trochanters, Knee joint centers, Posteriors of calcanei and Tips of the second toes

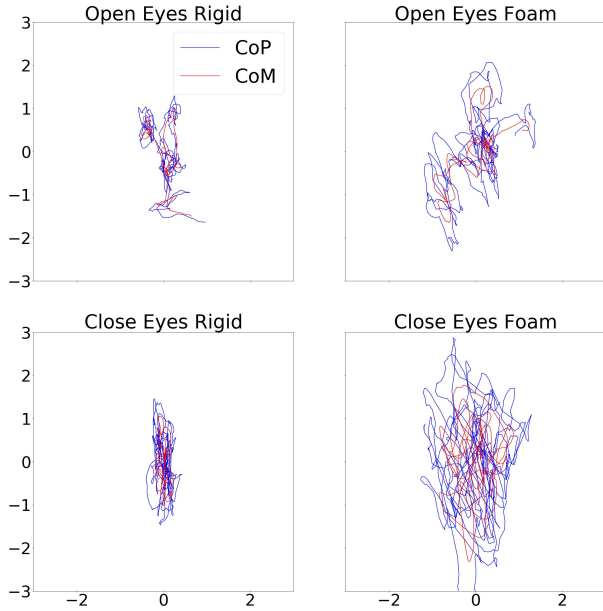


Fig. 1. Representative CoP / CoM trajectories. The figure shows the CoP excursion (blue) and the CoM excursion (red) from a representative participant with either eyes open (top) or eyes closed (bottom) on a rigid surface (left) and on a foam (right).

10 Hz cutoff frequency, in accordance to [23]. CoP position was calculated with the usual formula [38]:

$$\text{CoP}_x = \frac{-F_x c - M_y}{F_z} \quad \text{and} \quad \text{CoP}_y = \frac{-F_y c + M_x}{F_z},$$

where CoP_x (respectively CoP_y), F_x (resp. F_y), M_x (resp. M_y) denote the coordinates of the CoP, the ground reaction forces and the moments on the medio-lateral, resp. antero-posterior axis, F_z denotes the ground reaction force coordinates in the vertical axis, and c is the calibration parameter of the force platform. The resulting CoP trajectory was then centered.

Similarly, the COM trajectory was derived from the markers positions using the mass ratio coefficient defined in [36, Table 3.II]. The resulting three dimensional trajectory was then projected to the ground plane, centered, and processed with a fourth-order, zero-lag, low-pass Butterworth filter with a 10 Hz cutoff frequency. Finally, both the CoP and CoM trajectory were resampled at 20 Hz, corresponding to a Nyquist frequency of 10 Hz. Example of the resulting trajectories can be found in Figure 1.

D. Mathematical Model: Local Recall

As noted by previous works, the behaviour of the CoP trajectory shares important characteristics with a Wiener process [22]. However, representing the CoP by a Brownian motion implies that the CoP would exit the base of support in finite time, leading to a fall, which is in contradiction with the purpose of postural control. Therefore, previous studies have built on this remark by formulating the system as a Langevin model with additional forces, such as a damping or a spring restorative force [23]. In these works, the reference position for the spring restorative force is assumed to be static, and equal to the center of the base of support [29], or piecewise constant to model the shifting of weight between the feet [23].

However, it has been observed that the CoP tends to oscillate around the CoM, instead of a fixed central point. Consequently, in this study, we are interested in studying and evaluating the following model, called local recall, where the CoP is assumed to be solution of the stochastic differential equation:

$$d\mathcal{V}_t^{\text{CoP}} = \left[\underbrace{\Lambda (\text{CoM}_t - \text{CoP}_t)}_{\text{Recall}} + \underbrace{\Gamma (-\mathcal{V}_t^{\text{CoP}})}_{\text{Damping}} \right] dt + \underbrace{\Sigma}_{\text{Perturbations}} d\mathcal{B}_t \quad (1)$$

where CoM_t , CoP_t and $\mathcal{V}_t^{\text{CoP}}$ are respectively the two dimensional coordinates of the CoM, the CoP and the velocity of the CoP at time t , Λ , Γ , $\Sigma \in \mathbb{R}^{2 \times 2}$ are the coefficients matrices that characterize respectively the recall, damping and perturbations of the dynamic and \mathcal{B}_t is a two dimensional Wiener process. Note that (1) is similar to the classical Langevin equation.

Also, (1) simultaneously defines the dynamic of the CoP along the ML and the AP axes. The resulting dynamics in each axis can significantly differ, a well known phenomenon in postural control [16]. In this model, the ML and AP dynamics are assumed independent, thus Λ , Γ and Σ are diagonal. Therefore we can write $\Lambda = \begin{pmatrix} \Lambda_{\text{ML}} & 0 \\ 0 & \Lambda_{\text{AP}} \end{pmatrix}$ where Λ_{ML} and Λ_{AP} represent the components of the local recall force applying respectively on the ML and AP axis. Γ_{ML} , Γ_{AP} , Σ_{ML} and Σ_{AP} are defined similarly.

E. Parameters Estimation

Estimating the parameters Λ , Γ , Σ in (1) is key to the analysis of this model. Indeed, different values of each parameters will result in significantly different trajectories, and we do not assume that every individual will share identical dynamics. This is particularly important as the second population studied in this work includes both older adults that have fallen multiple times and healthy young individuals [35], two groups that have been shown to have different postural controls [20], [39]. Therefore, in order to assess the relevance of the local recall model, the task is double: first, the parameters of the model are estimated for each trajectory, using the recordings; and then the predictions of the model using these parameters are compared to the observed dynamic.

A significant difficulty regarding the parameter estimation is that while the model defined by (1) is continuous, the CoP and CoM trajectory are only observed at constant discrete time interval Δ_s (here $\Delta_s = 0.05$ s after resampling). To address this issue, we approximate the dynamic of the discrete trajectory of the CoP using (1) as follows:

$$\begin{cases} \text{CoP}_{t+\Delta_s} \approx \text{CoP}_t + \Delta_s \mathcal{V}_t^{\text{CoP}} \\ \mathcal{V}_{t+\Delta_s}^{\text{CoP}} \approx \mathcal{V}_t^{\text{CoP}} + \mathcal{N}(\Delta_s \mu_t, \Delta_s \Sigma^2) \end{cases} \quad (2)$$

with

$$\mu_t = \Lambda (\text{CoM}_t - \text{CoP}_t) + \Gamma (-\mathcal{V}_t^{\text{CoP}}) \quad (3)$$

Since CoM_t , CoP_t , and $\mathcal{V}_t^{\text{CoP}}$ are known from the recording, (2) and (3) define a linear model, where the unknown parameters are Λ and Γ . We use the Ordinary Least Square (OLS) method to estimate their respective values. More precisely, using the independence of the ML and AP dynamics,

$$\begin{pmatrix} \Lambda_{\text{ML}} \\ \Gamma_{\text{ML}} \end{pmatrix} = \mathbf{F}_{\text{ML}}^\dagger \mathbf{A}_{\text{ML}}, \quad (4)$$

where \dagger denotes the Moore-Penrose pseudo-inverse,

$$\mathbf{F}_{\text{ML}} = \Delta_s \begin{pmatrix} \text{CoM}_{\Delta_s, \text{ML}} - \text{CoP}_{\Delta_s, \text{ML}} & -\mathcal{V}_{\Delta_s, \text{ML}}^{\text{CoP}} \\ \dots & \dots \\ \text{CoM}_{n\Delta_s, \text{ML}} - \text{CoP}_{n\Delta_s, \text{ML}} & -\mathcal{V}_{n\Delta_s, \text{ML}}^{\text{CoP}} \end{pmatrix},$$

is the force matrix applied to the CoP, and

$$\mathbf{A}_{\text{ML}} = \begin{pmatrix} \mathcal{V}_{2\Delta_s, \text{ML}}^{\text{CoP}} - \mathcal{V}_{\Delta_s, \text{ML}}^{\text{CoP}} \\ \dots \\ \mathcal{V}_{n\Delta_s, \text{ML}}^{\text{CoP}} - \mathcal{V}_{(n-1)\Delta_s, \text{ML}}^{\text{CoP}} \end{pmatrix},$$

is the vector of observed speed variations.

Once Λ and Γ have been computed, we are also interested in estimating Σ , since this coefficient drives the perturbation force in the Langevin model (1). We estimate Σ as the unique positive square root of the empirical variance of the residuals divided by the sampling interval, that is:

$$\Sigma_{\text{ML}} = \sqrt{\frac{1}{n\Delta_s} \sum_{t=\Delta_s}^{n\Delta_s} (\mathbf{R}_{t, \text{ML}} - \bar{\mathbf{R}}_{\text{ML}})^2}$$

where

$$\hat{\mathbf{A}}_{\text{ML}} = \mathbf{F}_{\text{ML}} \begin{pmatrix} \Lambda_{\text{ML}} \\ \Gamma_{\text{ML}} \end{pmatrix}$$

is the predicted speed variation matrix,

$$\mathbf{R}_t = \mathbf{A}_{t, \text{ML}} - \hat{\mathbf{A}}_{t, \text{ML}}$$

is the residual of the model at time t , and $\bar{\mathbf{R}}_{\text{ML}}$ is the average value of the residuals. The same process can be repeated to obtain Λ_{AP} , Γ_{AP} and Σ_{AP} .

F. Model Analysis

All statistical analysis were performed following the recommendations of [40]. When reported, p-values were obtained using Mann-Whitney U-test with Bonferroni correction [41], and 95% confidence intervals for estimators were obtained using the 1.96 standard deviation half width.

1) Performance Evaluation: To evaluate the performance of the model, we proceeded as follows. For any given trajectory τ of length n , recall that \mathbf{A}_t and $\hat{\mathbf{A}}_t$ denote respectively the observed speed change of the CoP at time t and the expected speed change predicted by the linear model at time t . We computed the root mean square error (RMSE) of the prediction of speed variations $\mathcal{E}_{\text{ML}}(\tau)$, defined as

$$\mathcal{E}_{\text{ML}}(\tau) = \sqrt{\frac{1}{n} \sum_{t=\Delta_s}^{n\Delta_s} (\mathbf{A}_{t, \text{ML}} - \hat{\mathbf{A}}_{t, \text{ML}})^2},$$

We also computed $\tilde{\mathcal{R}}_{\text{ML}}^2(\tau)$, the adjusted coefficient of determination (adjusted R2) of the model [42]:

$$\begin{aligned} \mathcal{R}_{\text{ML}}^2(\tau) &= 1 - \frac{\sum_{t=\Delta_s}^{n\Delta_s} (\mathbf{A}_{t, \text{ML}} - \hat{\mathbf{A}}_{t, \text{ML}})^2}{\sum_{t=\Delta_s}^{n\Delta_s} (\mathbf{A}_{t, \text{ML}} - \bar{\mathbf{A}}_{\text{ML}})^2} \\ \tilde{\mathcal{R}}_{\text{ML}}^2(\tau) &= 1 - (1 - \mathcal{R}_{\text{ML}}^2(\tau)) \frac{n-1}{n-1-p}. \end{aligned}$$

where $\bar{\mathbf{A}}_{\text{ML}}$ is the average value of the observed speed change of the CoP and p is the number of predictor variables in the model. $\tilde{\mathcal{R}}_{\text{AP}}^2(\tau)$ and $\mathcal{E}_{\text{AP}}(\tau)$ are computed similarly. All the aforementioned quantities are calculated at the trajectory level, and we analysed the resulting distribution over trajectories. Using these metrics, we compared the accuracy of the local recall model to two others, to highlight the benefits of the local recall approach. In the first one, called global recall, the CoP is assumed to follow a Langevin dynamic similar to (1), except that the recall force pulls the trajectory towards the center of the base of support:

$$d\mathcal{V}_t^{\text{CoP}} = \left[\Lambda' (-\text{CoP}_t) + \Gamma' (-\mathcal{V}_t^{\text{CoP}}) \right] dt + \Sigma' dB_t$$

In the second one, called average model, we assume that the CoP acceleration can be directly approximated by the CoM acceleration:

$$d\mathcal{V}_t^{\text{CoP}} \approx d\mathcal{V}_t^{\text{CoM}} + \Sigma'' dB_t$$

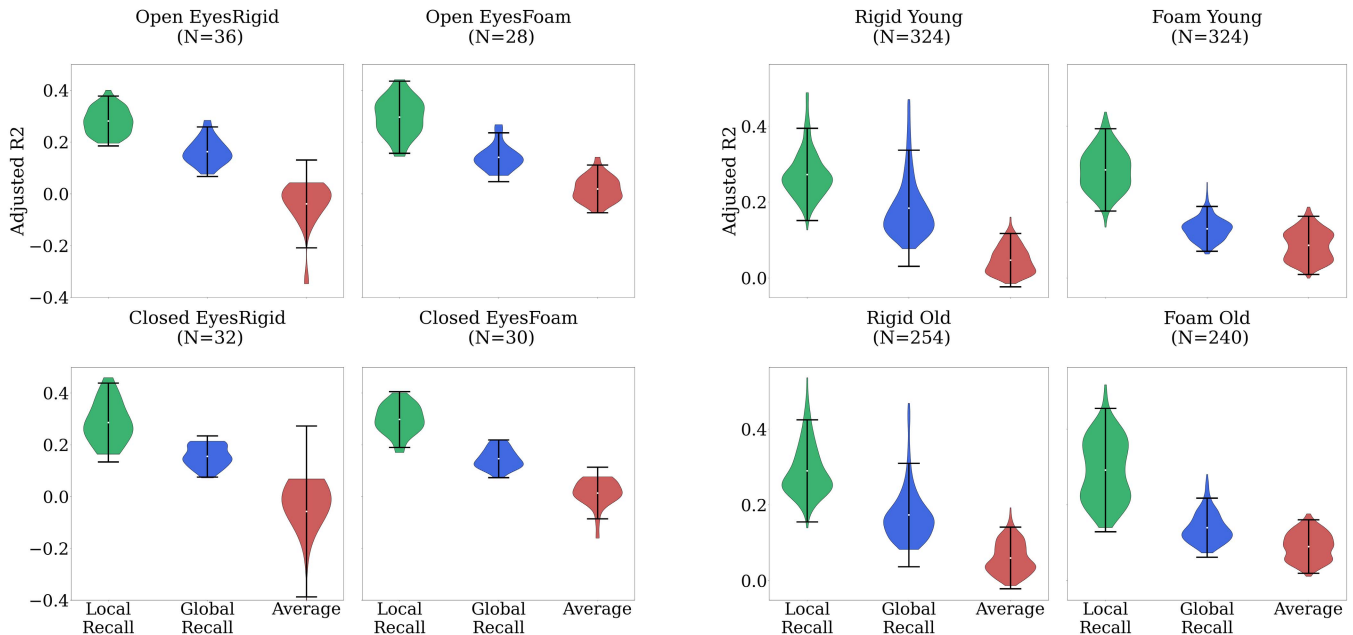
Note that Λ' , Γ' , Σ' and Σ'' were also estimated using the OLS algorithm.

2) Parameters Distribution: In a second part, we compared the distributions of the estimated parameters Λ , Γ , Σ of the local recall model for different groups of individual (such as healthy young individuals and older adults), as well as for different balance conditions (open eyes and closed eyes), to show that the values of these parameters may be indicative of different postural control profiles.

III. RESULTS

A. Model Evaluation

In all our analyses, the local recall model produced significantly larger values of explained variance (see Figure 2). As shown in Figure 2a, this improvement was observed for every recording condition of our experiment ($p < 10^{-8}$ compared to the global recall model, $p < 10^{-10}$ compared to the average model). Similar results were obtained on the larger population 2, which is the public dataset of [35] (Figure 2b, all respective p-values are $< 10^{-40}$). This is particularly



(a) Values of the adjusted R2 for population 1, for each of the four recording conditions: open eyes (top), closed eyes (bottom), rigid surface (left) and foam (right). ML and AP trajectories are jointly considered.

(b) Values of the adjusted R2 for population 2. Four subgroups are considered : Young age group (top), Older adults group (bottom), rigid surface (left) and foam (right). Open eyes and closed eyes conditions, as well as ML and AP trajectories, are jointly considered.

Fig. 2. Distribution of values of the adjusted R2 for the local recall model (green), the global recall model (blue) and the average recall model (red) on both populations. The whiskers indicate the 95% confidence interval. In every case, the adjusted R2 values for the local recall model are significantly larger than for the global recall model.

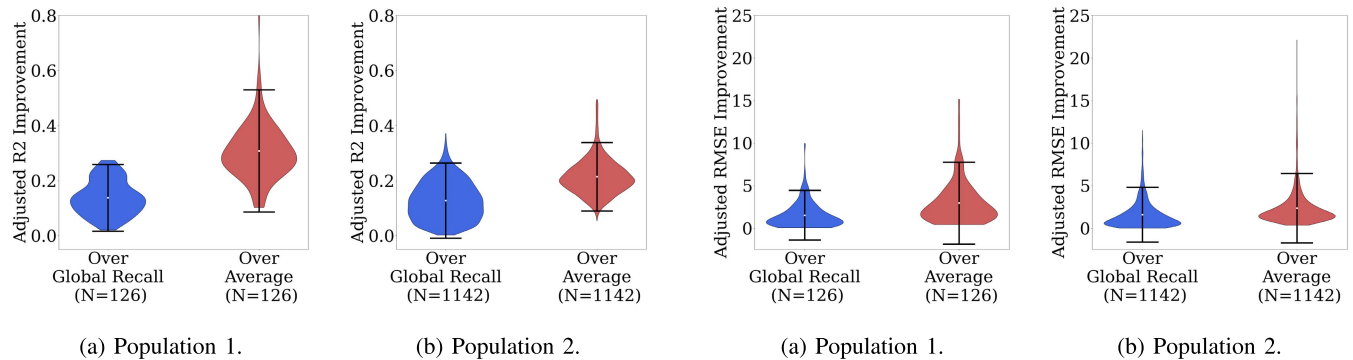


Fig. 3. Difference of the adjusted R2 between the local recall model minus respectively the global recall model (blue) and the average model (red) for each trajectory of both populations (left: population 1, right: population 2). The whiskers indicate the 95% confidence intervals. For every trajectory, the adjusted R2 difference is positive, highlighting the fact that the local recall model consistently produces better predictions.

Fig. 4. Difference of the RMSE between respectively the global recall model (blue) and the average model (red) minus the local recall model, for each trajectory of both populations (left: population 1, right: population 2). The whiskers indicate the 95% confidence intervals. For every trajectory, the RMSE difference is positive, indicating a lower RMSE for the local recall model.

interesting as the population included in this second dataset is larger and far more diverse, including young individuals and older adults, as well as individuals with a history of falls. It is also interesting to note that the average model, which tries to infer the acceleration of the CoP using solely the acceleration of the CoM, achieves adjusted coefficients of determination closed to zero, and significantly lower than the other models. This tends to show that while the CoP and CoM are closely related together, the CoP possesses its own dynamic that cannot be fully expressed by the CoM dynamic.

Further analyses show that this improvement occurs for every trajectory (Figure 3, $p < 10^{-20}$). Similar improvements were observed for the RMSE metric (see Figure 4, $p < 10^{-20}$). This confirms that the local recall model provides better predictions of the CoP dynamics, for every recording condition (open/closed eyes, rigid surface and foam) and for every individual.

B. Estimated Parameters Distribution

Table II reports the average and standard deviation of the estimated values of the parameters of the local recall model

TABLE II

AVERAGE (\pm STANDARD DEVIATION) OF THE ESTIMATED PARAMETERS FOR THE LOCAL RECALL MODEL FOR DIFFERENT EXPERIMENTAL CONDITIONS AND FOR DIFFERENT POPULATIONS: (TOP) POPULATION 1, (MIDDLE AND BOTTOM) POPULATION 2

Pop. 1	Units	Open Eyes Rigid	Closed Eyes Rigid	Open Eyes Foam	Closed Eyes Foam
Recall ML	s^{-2}	35.17(± 11.54)	34.74(± 11.85)	35.08(± 11.01)	35.87(± 7.73)
Recall AP	s^{-2}	43.85(± 11.27)	49.00(± 13.71)	47.72(± 12.87)	49.70(± 6.48)
Damping ML	s^{-1}	7.49(± 2.16)	6.81(± 2.08)	6.07(± 2.44)	5.93(± 1.76)
Damping AP	s^{-1}	7.11(± 1.76)	6.67(± 1.94)	5.72(± 2.12)	5.77(± 0.91)
Perturbation ML	$(cm \times s^{-2})$	1.37(± 0.53)	1.39(± 0.32)	2.72(± 0.78)	4.23(± 1.69)
Perturbation AP	$(cm \times s^{-2})$	2.36(± 0.73)	2.82(± 0.83)	4.40(± 1.50)	7.32(± 3.14)
Pop 2. Young individuals	Units	Open Eyes Rigid	Closed Eyes Rigid	Open Eyes Foam	Closed Eyes Foam
Recall ML	s^{-2}	40.32(± 8.11)	40.10(± 7.74)	37.91(± 6.25)	37.33(± 6.04)
Recall AP	s^{-2}	35.94(± 10.92)	39.86(± 11.42)	42.22(± 7.50)	48.85(± 9.21)
Damping ML	s^{-1}	9.74(± 3.73)	9.05(± 3.54)	4.49(± 1.10)	3.91(± 0.98)
Damping AP	s^{-1}	5.59(± 1.68)	5.03(± 1.46)	3.56(± 0.78)	3.96(± 1.08)
Perturbation ML	$cm \times s^{-2}$	1.96(± 0.27)	2.04(± 0.32)	3.06(± 0.45)	4.00(± 0.82)
Perturbation AP	$cm \times s^{-2}$	2.05(± 0.27)	2.27(± 0.40)	3.51(± 0.66)	5.82(± 1.65)
Pop 2. Older adults	Units	Open Eyes Rigid	Closed Eyes Rigid	Open Eyes Foam	Closed Eyes Foam
Recall ML	s^{-2}	35.21(± 6.90)	38.71(± 8.32)	31.53(± 5.40)	32.85(± 6.71)
Recall AP	s^{-2}	43.39(± 9.22)	47.26(± 11.79)	50.33(± 8.23)	55.67(± 12.47)
Damping ML	s^{-1}	8.20(± 3.39)	7.68(± 3.72)	3.45(± 0.94)	3.63(± 1.05)
Damping AP	s^{-1}	4.86(± 1.82)	4.75(± 1.86)	4.07(± 1.15)	4.43(± 1.31)
Perturbation ML	$cm \times s^{-2}$	2.03(± 0.33)	2.19(± 0.43)	3.54(± 0.83)	4.76(± 1.56)
Perturbation AP	$cm \times s^{-2}$	2.41(± 0.53)	2.93(± 0.70)	5.96(± 1.65)	9.51(± 3.59)

– Λ , Γ and Σ – for different recording conditions and different groups of individuals. Interestingly, the perturbation coefficient Σ generally increases as the *expected* quality of the postural control decreases. For instance, AP perturbations for young individuals on rigid surface with open eyes 2.05(± 0.27) are significantly lower than the values for young individuals on foam surface with closed eyes 5.82(± 1.65) ($p < 10^{-20}$), which in turn are lower than the values for older adults on foam surface with closed eyes 9.51(± 3.59) ($p < 10^{-8}$). This relation is further explored in Figure 5, where it can be seen that this phenomenon is observable on both populations. Moreover, while no significant variations of Γ_{AP} are observed, Γ_{ML} shows an important decrease on Pop 2. for individuals on foam surfaces compared to individuals on rigid surfaces ($p < 10^{-10}$). Note however that this difference is not observed on Pop 1 (see Figure 6). Conversely, the local recall coefficient Λ does not vary significantly between recording conditions. While a mild increase is observed on the AP axis between individuals on rigid surfaces and foam surfaces for Pop. 2 ($p < 0.01$), further analyses show strong overlap of the confidence intervals (see Figure 7). Therefore, these observations are insufficient to conclude in either direction.

IV. DISCUSSION

In the first part of the analyses we compared the accuracy of the predictions of three models: the global recall model, where the CoP follows a Langevin dynamic whose sole equilibrium

point is the center of the force platform; the local recall model, where the CoP is assumed to follow a Langevin dynamic with the CoM position as non-static attachment point; and the average model, which assumes that the CoP acceleration is driven solely by the CoM acceleration.

The results of the analyses showed that the local recall model provided significantly better predictions of the CoP dynamic than its two counterparts. This is particularly true for the average model, whose accuracy is the lowest, which tends to show that the CoP acceleration cannot be approximated by the CoM acceleration. However, the analyses also showed that by adding information about the CoM position in the Langevin model, the local recall model produces better estimates of the CoP dynamic than the global recall model. This result suggests that the trajectory of the CoM is important to understand the CoP dynamic, and that the Langevin model may provide relevant insights into the CoP behavior with respect to the CoM. Crucially, the predictions accuracy improvement was consistent, and occurred for each trajectory of both datasets, regardless of the protocol or of individual characteristics.

This observation that the CoM is key to understand the CoP dynamic is in line with the results discussed by previous works. In [31] a method was proposed to decompose the CoP trajectory in two components, rambling and trembling, where the latter is assumed to reflect the oscillations of the CoP around a reference point trajectory. In their findings, the authors mentioned that this reference trajectory – computed

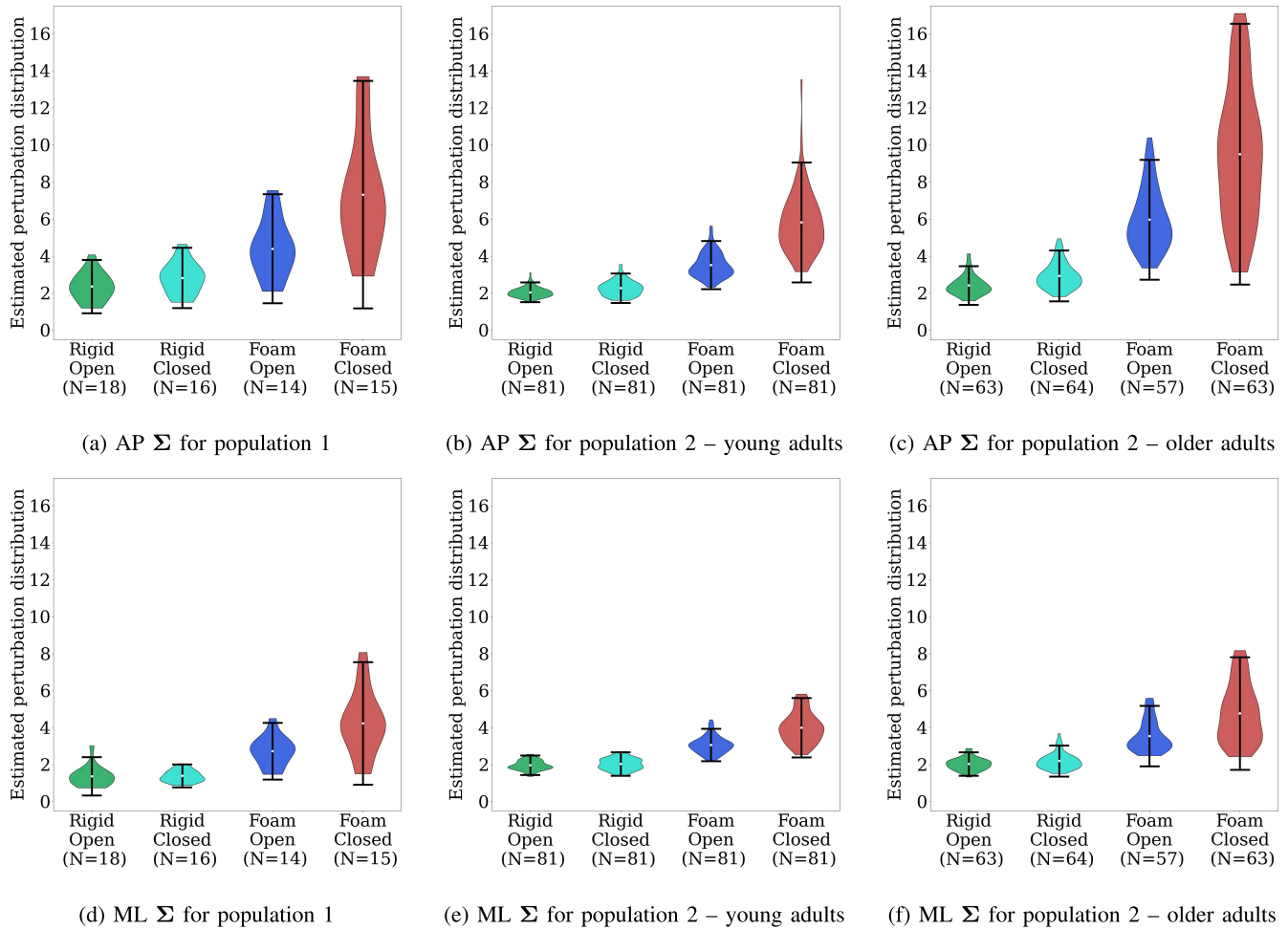


Fig. 5. Distribution of the estimated perturbation coefficient in the local recall model for different conditions (green: open eyes rigid surface, cyan: closed eyes rigid surface, blue: open eyes foam and red: closed eyes foam), different populations (left: Population 1, middle: young individuals of population 2, right: older adults of population 2) and different axes (top: antero-posterior, bottom: medio-lateral). The whiskers indicate the 95% confidence interval. Average values of the 6 parameter significantly increase as the expected balance deteriorates.

as the interpolation of the CoP points at which the horizontal force resultant vanishes – is very close to the CoM trajectory, and this result can be seen as hinting at the possibility that the CoM might be a reference point around which the CoP gravitates. In [15] the authors introduced a model based on the inverted pendulum that relies on the assumption that muscles of the ankle act as springs to cause the CoP to control the body deviations from the vertical. This hypothesis has been successfully applied to continuous linear feedback controllers such as PID (Proportional, Integral, Derivative) systems [11], [33], [34]. In these works the CoM is central to the model, as the forces to maintain posture are modeled by springs dependent on both body angle and body angular velocity, which can be assumed approximatively proportional to the CoM position and speed for small body angles.

In our model the mediolateral and anteroposterior components are assumed to have distinct dynamics. This assumption is important considering the significant differences in balance control observed in each axis through the characteristics of the CoP [16] or the different muscles involved [15]. However, we additionally assume that those dynamics are independent. While this assumption is a commonly used

approximation [22], previous works [27] have proposed models where the dynamic of the postural control is influenced by the radius, i.e. the distance between the CoP and the center of the base of support. As the radius inherently depends simultaneously on both the AP and ML coordinates, such phenomenon cannot be captured by the local recall model, and studying extensions of the model that can embed possible axes interdependence seems an interesting research direction.

It should be noted that RMSE and R2, while providing important information, are not perfect metrics to evaluate the accuracy of one model. Indeed, the problem of measuring goodness-of-fit is still an open research topic (see e.g. [43]). Consequently, while observed results tend to show that the local recall model is better than its two counterparts, i.e. at a relative scale, it is significantly harder to assess how good the model is on an absolute scale. For instance, model residuals are ambivalent as they encompass both model errors, i.e. inaccurate predictions, as well as the Brownian perturbations that can be part of the postural control system. Previous works have considered alternative approaches to validate models, such as bootstrapping. This method uses a generative model to assess the likelihood of the observed characteristics on

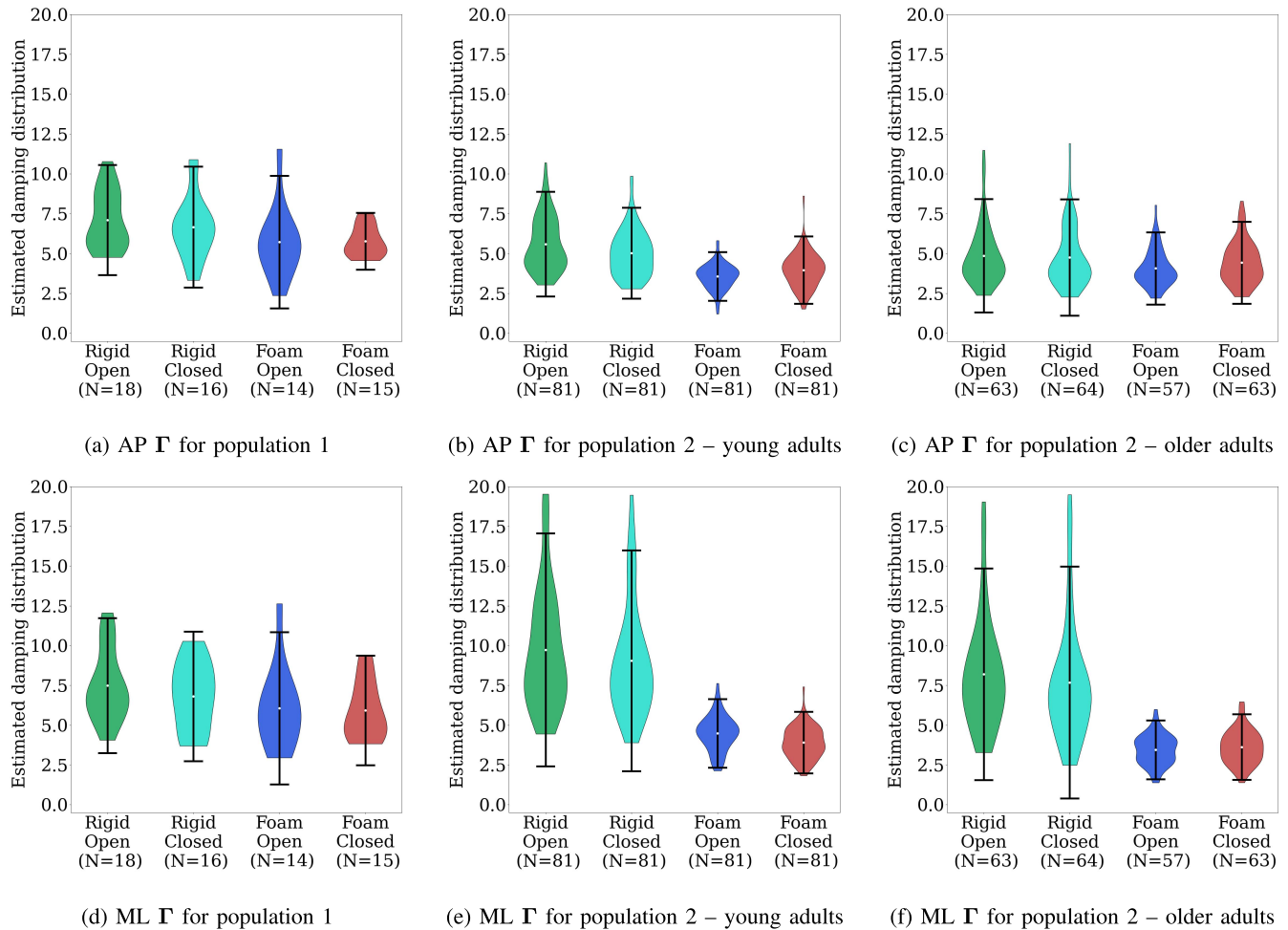


Fig. 6. Distribution of the estimated damping coefficient in the local recall model for different conditions (green: open eyes rigid surface, cyan: closed eyes rigid surface, blue: open eyes foam and red: closed eyes foam), different populations (left: Population 1, middle: young individuals of population 2, right: older adults of population 2) and different axes (top: antero-posterior, bottom: medio-lateral). The whiskers indicate the 95% confidence interval. While no significant variations are observed in Population 1, σ_{ML} significantly decreases between the rigid and foam conditions in Population 2.

the original signals compared to the characteristics of the generated ones. Recently, this method of validation has been applied on a Langevin equation of the CoP [26]. Unfortunately, this approach requires the choice of specific characteristics of the CoP, a choice which can have a significant influence on the results, and also necessitates a joint generative model of both the CoP and the CoM. Nevertheless, this is an interesting future direction for this research.

Interestingly, the parameter Λ , which encodes the strength of the recall force in the local recall model, does not significantly vary between different groups and protocols in our experiments. In previous works, the recall parameter has been interpreted as related to the ankle joint stiffness [23], [29], which is defined as the derivative of the torque applied at the ankle with respect to the angle of deviation from the gravity line [30]. However, Langevin models do not explicitly incorporate ankle stiffness and further work is required to link quantitatively the recall parameter to biomechanics components.

Conversely, the parameter Γ , which measures the strength of the damping, i.e. the force which opposes to the velocity of the

system, was shown in our experiments on Pop 2. to decrease in the ML axis when going from a rigid surface to a foam surface. This result shows that this force, preventing the velocity of the body becoming too strong, is a component of postural control that can be vulnerable to sensorial perturbations induced by unstable surfaces [44], and thus be indicative of some specificities in sensorimotor profile. The fact that this result is not observed on Pop 1. could be explained by some differences existing between the type of foam used in each dataset.

Finally, the parameter Σ appears to strongly increase when the expected balance quality decreases in our experiments. The interpretation of the perturbation force is more complicated, as it can be representative of two distinct phenomena. On the one hand, Σ corresponds to the coefficient of diffusion associated with the Brownian process ΣB_t and therefore may be associated with the strength of the stochastic activity in the postural system, which has been suggested to increase with ageing [45]. These perturbations may arise from various sources such as breathing [24], [46] or from any errors in sensori-motor integration or postural adjustments. On the other hand, $\Sigma \delta B_t$ also represents the noise in the formalization of

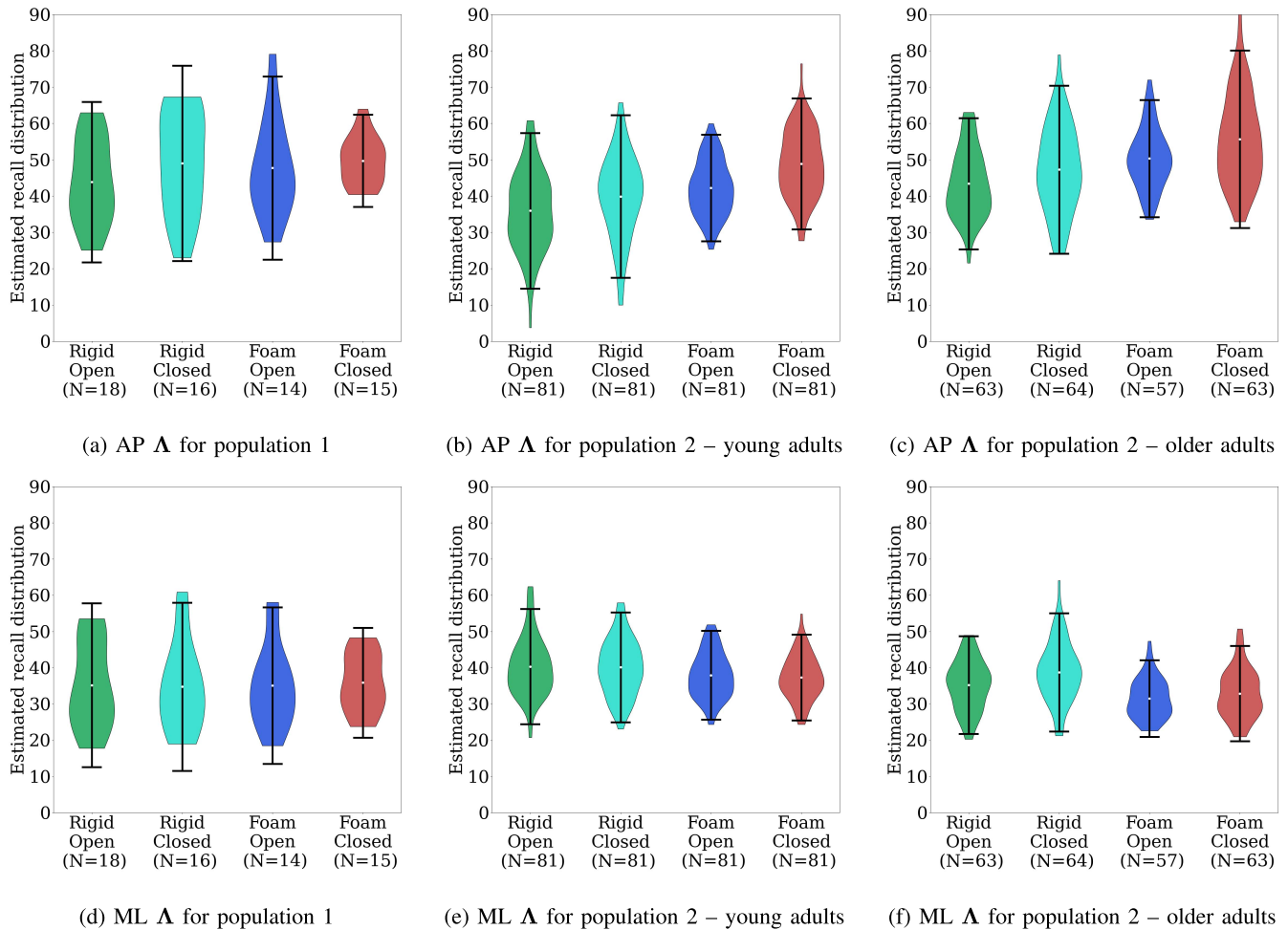


Fig. 7. Distribution of the estimated recall coefficient in the local recall model for different conditions (green: open eyes rigid surface, cyan: closed eyes rigid surface, blue: open eyes foam and red: closed eyes foam), different populations (left: Population 1, middle: young individuals of population 2, right: older adults of population 2) and different axes (top: antero-posterior, bottom: medio-lateral). The whiskers indicate the 95% confidence interval. No significant variations of Λ are observed in either populations.

the linear model, and therefore can include the fitting error of the model. Consequently the parameter Σ may also reflect a wrong adjustment to the local recall model. In both views, large components of Σ for a trajectory in comparison to other individual's trajectories could be the sign of a bad balance, either because of a perturbed postural control, or because the individual does not share the same postural control dynamics as others, which could be explained by the existence of age-dependent postural control strategies [45].

V. CONCLUSION

In conclusion, this study showed that the dynamic of the CoP is strongly influenced by the trajectory of the CoM, and that the spring restorative force that is part of Langevin models for quiet stance should be aimed toward to the CoM position, instead of the center of the base of support. We showed that this modified model, called local recall, significantly increased the accuracy of the prediction of the CoP Langevin model, providing interesting research directions for future postural control models. Additionally, we provided a method to estimate the parameters of the local recall model, and showed that key parameters (damping, perturbations) are

closely correlated with the quality of postural control. Finally, these findings support the hypothesis that the Langevin model has the potential to quantify interesting aspects of postural control, and could be significantly improved by the embedding of the CoM trajectory. Further work is needed to link precisely the parameters of the local recall model to biomechanical components of postural control as well as to investigate if other improvements of the model, such as the addition of nonlinearities [47] or intermittent postural adjustments [24], could lead to a more realistic quantification of postural control.

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