Does ankle push-off correct for errors in anterior-posterior foot placement relative to center-of-mass states?

Jian Jin[1], Jaap H. van Dieën[1], Dinant Kistemaker[1], Andreas Daffertshofer[1,2], Sjoerd M. Bruijn[1,2]

[1] Department of Human Movement Sciences, Faculty of Behavioural and Movement Sciences, Vrije Universiteit Amsterdam, Amsterdam Movement Sciences, Amsterdam, The Netherlands

[2] Institute of Brain and Behavior Amsterdam, Amsterdam, The Netherlands

Corresponding Author:

Sjoerd M. Bruijn

Van der Boechorststraat 9, 1081 BT Amsterdam, The Netherlands

Email address: s.m.bruijn@vu.nl

Abstract

43 **Abstract**
44 Understanding the mechanisms humans use to stabilize walking is vital for predicting falls in
45 elderly. Modeling studies identified two potential mechanisms to stabilize gait in the anterior-
46 posterior direction: foot placement control and ankle push-off control: Foot placement depends
47 on position and velocity of the center-of-mass (CoM) and push-off covaries with deviations
48 between actual and predicted CoM trajectories. While both control mechanisms have been
49 reported in humans, it is unknown whether especially the latter one is employed in unperturbed
50 steady-state walking. Based on the finding of Wang and Srinivasan that foot placement deviates
51 in the same direction as the CoM states in the preceding swing phase, and assuming that this
52 covariance serves the role of stabilizing gait, the covariance between the CoM states and foot
53 placement can be seen as a measure of foot placement accuracy. We subsequently interpreted the
54 residual variance in foot placement from a linear regression model as "errors" that must be
55 compensated, and investigated whether these foot placement errors were correlated to push-off
56 kinetic time series of the subsequent double stance phase. We found ankle push-off torque to be
57 correlated to the foot placement errors in 30 participants when walking at normal and slow
58 speeds, with peak correlations over the double stance phase up to 0.45. Our study suggests that
59 humans use a push-off strategy for correcting foot placement errors in steady-state walking.

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Introduction

81 Walking is a seemingly simple task for most of us. Yet, it involves intricate feedback control and
82 an ongoing integration of sensory inputs and generation of motor outputs (Rossignol et al., 2006;
83 Warren et al., 2001; Zehr & Stein, 1999). A solid understanding of the mechanisms that underlie
84 the stabilization of walking is crucial for identifying causes of falls in elderly (McGibbon, 2003).
85 In-silico studies singled out basic principles of locomotion. Two examples are feedback control
86 of foot placement and of ankle push-off. Both of these mechanisms have been shown to stabilize
87 comparably simple walking models in the presence of perturbations. For instance, Hobbelen &
88 Wisse (2008) illustrated that modulating ankle push-off torque via feedback from the leading
89 leg's angle substantially improved robustness against perturbations in a sagittal plane flat-feet
90 walker. According to Byl & Tedrake (2008), feedback-controlled foot placement with a constant
91 push-off magnitude appears more robust than merely modulating the push-off magnitude in a
92 point-feet walker model. In addition, in inverted pendulum models, a combined foot placement
93 and push-off control based on feedback from mid-stance speed demonstrated good robustness
94 (Bhounsule, 2015; Kelly & Ruina, 2015; Zaytsev et al., 2018). Also in human walking, one can
95 find ample evidence that foot placement is based on CoM position and/or velocity. This applies
96 to both steady-state (Redfern & Schumann, 1994; Wang & Srinivasan, 2014) and perturbed
97 walking (Joshi & Srinivasan, 2019; Vlutters et al., 2018b). Moreover, after a perturbation, ankle
98 push-off seems to modulate with deviations of CoM trajectories from the desired trajectories
99 (Afschrift et al., 2021; Fettrow et al., 2019; van Mierlo et al., 2021; Vlutters et al., 2016). Thus
100 far this evidence is restricted to perturbed walking, but we here subsume that humans also use a
101 feedback-controlled push-off strategy to stabilize steady-state walking.

102   In human walking, foot placement along the anterior-posterior (AP) direction is correlated to
103 CoM states, i.e., CoM position and velocity. Wang & Srinivasan (2014) showed that CoM states
104 at mid-stance and heel strike predict about 33% of the variance in AP foot placement. Recently,
105 Liu (2021) replicated this finding in steady-state walking and additionally in perturbed walking.
106 This study by Liu revealed that a different foot placement model is needed to describe responses
107 to slip-like and trip-like treadmill perturbations, suggesting that the control of foot placement
108 may be different between steady-state and perturbed walking. By the same token, ankle push-off
109 during the double stance phase seems to modulate with AP pelvis perturbations: van Mierlo et al.
110 (2021) found adjustments of the double stance duration and the AP center-of-pressure (CoP)
111 trajectory to correct perturbed CoM states towards desired states at the end of the double stance
112 phase; and, Afschrift et al. (2021) demonstrated that for AP pelvis perturbations and for treadmill
113 belt speed perturbations, the deviations in CoM states from the steady-state trajectory accurately
114 predicted the ankle moment after a neural delay of about 100 ms. In steady-state walking, the
115 percentage of explained variance of AP foot placement from the CoM states increased from 33%
116 to 70% during the double stance phase (Wang & Srinivasan, 2014). That is, there may be
117 modulations of the CoM states through ankle push-off control.

118   Since CoM states covary with AP foot placement, either one does not suffice as the input for
119 push-off control. Instead, more appropriate feedback signals would integrate both terms,

120   representing the covariance between the CoM states and foot placement, or *foot placement error*,
121   first introduced by van Leeuwen and co-workers, (2021). It is defined as the difference between
122   the actual foot placement and the ideal foot placement based on the CoM states at heel strike.
123   This can be estimated by linearly regressing CoM states with foot placement (Wang &
124   Srinivasan, 2014). Maintaining the covariance between the CoM states and foot placement has
125   been suggested to be a useful control strategy for gait stability both in simple walking models
126   (Hof, 2008; Joshi & Srinivasan, 2019; Maki & McIlroy, 1999; Townsend, 1985) and in humans
127   (Joshi & Srinivasan, 2019; Redfern & Schumann, 1994; Verrel et al., 2010; Wang & Srinivasan,
128   2014). Assuming the presence of foot placement control, residual variance in foot placement
129   from a linear regression model can be viewed as foot placement *errors* that must be corrected.
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131   [Figure 1 goes here]
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133   As shown in Figure 1, a positive foot placement error in the AP direction indicates that foot is
134   placed more forward with respect to a linear prediction from the CoM states. In this case, there is
135   a higher collision loss due to larger step length (Adamczyk & Kuo, 2009), and the walker's post-
136   collision total energy will be lower, requiring a stronger push-off from the trailing leg and/or
137   from the hip extension torque via the leading leg to compensate for this larger collision loss.
138   Here, we assumed the collision loss to be balanced by the push-off work on the CoM during the
139   double stance phase, as observed in human walking (Kim & Park, 2012). We hence expected the
140   push-off force/torque magnitude to be proportional to the AP foot placement error, i.e., a
141   stronger push-off for larger positive foot placement errors, and a weaker push-off for more
142   negative foot placement errors.
143   We examined push-off modulations by investigating how kinetic time series were modulated
144   during the double stance phase as a function of the foot placement error. Next, we evaluated the
145   correlations between foot placement errors and three kinetic time series: the combined AP
146   ground reaction force (GRF), the trailing leg's AP GRF, and the trailing leg's ankle moment. The
147   kinetic time series were chosen instead of the (scalar) kinematic variables like work or impulse
148   because the kinetic pattern could serve to illuminate the mechanisms related to the correction of
149   foot placement errors. We did not select ankle power as outcome measure mainly because ankle
150   power is determined by ankle moment and angular velocity, and modeling studies (Bhounsule,
151   2015; Hobbelen & Wisse, 2008; Kelly & Ruina, 2015; Zaytsev et al., 2018) suggested that
152   modulating the magnitude of ankle push-off moment without joint angular velocity input was
153   sufficient for improving gait robustness. For every participant, we also compared the mean
154   kinetics of ten most positive foot placement errors with the mean kinetics of ten most negative
155   foot placement errors to study how the push-off may differ when correcting positive and negative
156   foot placement errors. We selected the combined AP GRF because it represents the summed
157   effect of ankle push-off by the trailing leg and braking by the leading leg. The use of the trailing
158   leg's AP GRF was motivated by the idea that the CoM is mainly accelerated via the trailing leg's
159   AP GRF (Hernández et al., 2009). The use of ankle moment was motivated by modeling studies

160 that indicated ankle push-off to stabilize gait (Hobbelen & Wisse, 2008; Kerimoglu et al., 2021;
161 Kim & Collins, 2017) and to provide the bulk of the trailing leg's propulsive force (Franz &
162 Kram, 2014). This is due to a higher gain from ankle moments to the trailing leg's AP GRF
163 compared to hip or knee moments (Biewener et al., 2004; Toney & Chang, 2016).

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Methods

166 We used existing data from steady-state normal and slow treadmill walking experiments (van
167 Leeuwen et al., 2020a & 2020b). Below, we briefly sketch data collection and processing but we
168 refer to van Leeuwen et al., (2020a) for more details. The data can be found at
169 https://doi.org/10.5281/zenodo.4229851 and the code can be found at
170 https://zenodo.org/record/7393791#.Y43Gvy2ZOqQ.
171   **Participants**. 30 participants were included (19 female, 11 male, age 30 ± 7 years, weight
172 70 ± 13 kg, height 1.73 ± 0.08 m; mean $\pm$ sd). None of them reported injuries or balance issues
173 that could affect their gait pattern. All participants signed informed consent before the
174 experiment. Ethical approval (VCWE-2018-159) had been granted by the ethics board of the
175 Faculty of Behavioural and Movement Sciences, Vrije Universiteit Amsterdam, prior to
176 conducting the experiment.
177   **Protocol**. Every participant walked on a treadmill at a constant belt speed of $v = 0.4\sqrt{gl}$ m/s
178 (*normal* walking condition) and $v = 0.2\sqrt{gl}$ m/s (*slow* walking condition), with $g = 9.81$ m/s^2
179 being the gravitational constant and l the leg length. A metronome served to impose stride
180 frequency to minimize stride frequency variations. Participants were asked to match their right
181 heel strikes to the beat. The imposed frequency during normal/slow trials was customized as the
182 average preferred stride frequency during the last hundred steps of the familiarization trial
183 without metronome at each speed. The normal walking trials lasted five and the slow walking
184 trials ten minutes each to ensure that data of at least 200 consecutive strides were collected.
185 Normal and slow speed trials were randomized in order and separated by sufficient breaks to
186 prevent fatigue.
187   **Data collection and processing**. Participants walked on an instrumented dual-belt treadmill
188 (Motek-Force-link, Amsterdam, Netherlands). Full-body kinematics were recorded using an
189 active 3D motion analysis system and cluster markers on all segments (Optotrak, Northern
190 Digital Inc, Waterloo ON, Canada). For every participant and condition, we analyzed the last 200
191 consecutive strides without data quality issues (e.g., limited marker visibility, large noise, etc.).
192 GRF data were collected using a force plate integrated in the treadmill. Gait events (heel strike
193 and toe-off) were detected based on the so-called "butterfly pattern" of the combined CoP
194 trajectory. This method, validated by Roerdink et al., (2008), has the advantage that it does not
195 require the setting of an ad-hoc threshold. The trajectories of the segments and the kinematics
196 were calculated using a 3D linked segmented model (Kingma et al., 1996) based on the
197 coordinates of markers and anatomical landmarks. The kinetics, including ankle moments in the
198 sagittal plane, was calculated from the measured GRFs and the lower body kinematics using
199 bottom-up inverse dynamics (Hof, 1992; Kingma et al., 1996). For subsequent analysis, the

200 kinematic and kinetic time series of a step/stride (defined from heel strike to
201 contralateral/ipsilateral heel strike) were time-normalized. We accounted for the variations in
202 timing of heel strike and subsequent push-off within a step[1] by segmenting the time window of a
203 step to single-stance and double stance sub-windows with fixed time length per walking
204 condition.

205   **Linear foot placement model**. Similar to previous studies (van Leeuwen et al., 2020a; Wang
206 & Srinivasan, 2014), we fitted a linear model between the CoM states and AP foot placement.
207 This full body CoM state was derived from a weighted sum of the body segments' CoM, which
208 in turn was estimated from the percent longitudinal distances of the body segments' CoM to
209 neighboring bony landmarks, relative to the lengths of respective segments (de Leva, 1996). The
210 predictor CoM states included the AP position (the horizontal distance from stance foot to CoM)
211 and the AP velocity, i.e., COM_{pos} and COM_{vel}, respectively. The predictor and dependent
212 variables were de-meaned prior to regression to ensure a zero intercept. The linear foot
213 placement model reads as follows:

$$FP_i(j = 100\%) = \beta_{pos}(j) \cdot CoM_{pos,i}(j) + \beta_{vel}(j) \cdot CoM_{vel,i}(j) + \varepsilon_{FP,i}(j), \tag{1}$$

214 which predicts AP foot placement at heel strike $FP_i(j = 100\%)$ based on CoM AP position
215 $CoM_{pos,i}(j)$ and velocity $CoM_{vel,i}(j)$ at step i and phase j. More specifically, FP_i represents the
216 (de-meaned) AP distance between the trailing and leading leg in step i, $\beta_{pos}(j)$ and $\beta_{vel}(j)$ are the
217 phase-dependent regression coefficients obtained from the least square fit, and $\varepsilon_{FP,i}(j)$ denotes
218 the phase-dependent residual from the linear regression. The variable j indicates the (normalized)
219 phase in a step (0-100% from heel strike to contralateral heel strike). We used the phase instant
220 at heel strike (100%) to compute the foot placement FP_i and the foot placement error $\varepsilon_{FP,i}$, which
221 we assume to be corrected by the subsequent push-off, see below.

222   **Correction of foot placement error**. Using regression analysis, we evaluated how well the
223 foot placement error at heel strike correlated to the combined AP GRF, the trailing leg's AP
224 GRF, and the trailing leg's ankle moment during the double stance. The general model relating
225 foot placement errors and the subsequent kinetic time series (indicated by F) was defined as:

$$F_{i+1}(j) = \beta_{\varepsilon_{FP}}(j) \cdot \varepsilon_{FP,i}(j = 100\%) + \varepsilon_{i+1}(j), \tag{2}$$

226 where $\beta_{\varepsilon_{FP}}(j)$ is the phase-dependent linear regression coefficient, and $\varepsilon_{i+1}(j)$ is the residual of
227 the new linear regression. The step index $i + 1$ was used because we intended to investigate
228 whether the foot placement error $\varepsilon_{FP,i}$ at the end of previous step i was corrected by the kinetic
229 variables in the subsequent step F_{i+1}, in particular during the double stance phase. However,
230 given that the ankle push-off moment could potentially begin before contralateral heel strike, and
231 that the stored elastic energy during the preceding ankle plantarflexion is released during ankle

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[1] The total samples of time window for the single stance phase, double stance phase in normal and slow walking
     were different on average (over all steps from all participants).

232 push-off and influences the ankle extension moment, we also replaced step index $i + 1$ by i in
233 Equation 2 to investigate the kinetic time series earlier than the heel strike. As such, we included
234 and analyzed the kinetic time series of a complete stride.
235   We selected three types of kinetic variables F to correlate with foot placement errors ε_{FP}: 1)
236 combined AP GRF, which represents the sum of anterior-posterior GRF at both legs, with larger
237 positive values indicating a larger forward GRF; 2) trailing leg's AP GRF; 3) trailing leg's ankle
238 moment, with positive values indicating an internal plantar-flexion moment. All position
239 coordinates were defined with respect to the stance foot (trailing foot). As illustrated in Figure 1,
240 a larger positive foot placement error indicates a more forward foot placement location than the
241 linear prediction from the CoM states. We expected positive correlations between foot placement
242 errors and kinetic time series (F) during the subsequent double stance phase, i.e., a larger
243 combined/trailing leg's AP GRF or ankle moment for a larger positive foot placement error, and
244 vice versa. We assume the resulting correlations to suggest feedback control. Yet, we have to
245 admit that correlations may also arise from passive dynamics (Patil et al., 2019) or from intrinsic
246 muscle properties (e.g., preflexes stabilizing movements through nonlinear viscoelastic
247 properties of muscles when in contact; cf. Loeb, 1995). We return to this in the Discussion
248 section.
249   In addition to the regression analysis, we compared the kinetic time series of the "most
250 positive" with that of the "most negative" foot placement errors. Specifically, the foot placement
251 errors of each participant (200 strides) were sorted from low to high, and the ten most positive
252 and ten most negative foot placement error strides were analyzed, by extracting the mean kinetic
253 time series from these sets of ten strides.
254   **Statistics**. All statistical tests and analysis were performed in Matlab (v2017b, The
255 Mathworks Inc., Natick, MA), including the multi-linear regression of the foot placement model.
256 Correlation values are presented as group level means and individual data. The mean correlations
257 were obtained by 1) first applying Fisher's r-to-z transform to guarantee the normality of the
258 correlation coefficients; 2) then averaging the z-values over all participants per condition; and,
259 3), inverting the Fisher transform to obtain the group mean correlation coefficients per condition.
260 We tested the correlation coefficients for significance using statistical parametric mapping
261 (Friston et al., 2007) as implemented in the SPM1D toolbox (https://spm1d.org/). In brief,
262 SPM1D allows for statistical testing of time series data, considering the interdependence
263 (smoothness) between time samples. To test for differences between the kinetic time series of the
264 "most positive" and "most negative" foot placement errors, we also performed an SPM1D paired
265 t-test. The significance level of every test was set to $\alpha = 0.05$.
266
Results
268 The variance in AP foot placement explained by the CoM states (R^2) increased over the single
269 stance phase (Fig. 2, left of the dashed vertical line) and reached values between 50% and 80%
270 during the double stance phase in both normal and slow walking (Fig. 2, right of the dashed
271 vertical line). Regression coefficients for CoM AP velocity were larger than for AP position

272 (Supplemental Figure S1). The significance of the correlation coefficients for all 30 participants
273 was also presented in Supplemental Figure S1, which showed that the linear foot placement
274 model (Equation 1) reached significance in the majority phases from toe-off to contralateral toe-
275 off for the majority of participants. Note that in order to demonstrate foot placement accuracy, a
276 step here in Figure 2 was defined from toe-off to contralateral toe-off instead of from heel strike
277 to contralateral heel strike which was defined in Equations 1 and 2.

278

279 [Figure 2 goes here]

280

281   Although a large proportion of foot placement variance could be explained by the CoM states
282 at heel strike, a fair amount of unexplained variance remained, i.e., there were substantial foot
283 placement errors. The distributions of foot placement errors across all participants for normal and
284 slow walking were close to Gaussian with zero mean (Fig. 3a). Note that zero mean of the foot
285 placement errors is the result of the de-meaned FP. The variance of foot placement errors in slow
286 walking was larger than in normal walking (Fig. 3a). The group means of the 10 most positive
287 and 10 most negative foot placement errors in slow walking had larger magnitudes compared to
288 those in normal walking (Fig. 3b).

289

290 [Figure 3 goes here]

291

292   Across participants, the foot placement errors at heel strike were correlated with the combined
293 AP GRF during the subsequent double stance phase in normal and slow walking (peak mean
294 correlations over participants up to 0.34 and 0.28, respectively; see Fig. 4a). The significance of
295 such correlation coefficients for all 30 participants was presented in Supplemental Figure S2,
296 which showed that the correlation coefficients reached significance in early phases of the double
297 stance phase for all except one participant in slow walking (participant 08). High positive
298 correlations occurred in the first half of the double stance phase and decreased to negative
299 correlations over the latter half of the double stance phase. Correlations were close to zero prior
300 to foot placement, which implies that foot placement can hardly be predicted based on the
301 combined AP GRF prior to foot placement. Correlations were also close to zero at foot
302 placement. This suggests that preemptive push-off indicated by the combined AP GRF did not
303 cause foot placement errors. Correlations were significant and negative at the end of the stride
304 cycle during normal walking (before the subsequent heel strike, mean correlations reached -0.43,
305 see Fig. 4a and Supplemental Figure S2).
306   Likewise, the foot placement errors at heel strike were correlated with the trailing leg's AP
307 GRF during the subsequent double stance phase in normal and in slow walking (peak mean
308 correlations over participants up to 0.45 and 0.41, respectively; see Fig. 4b). The significance of
309 such correlation coefficients for all 30 participants was presented in Supplemental Figure S3,
310 which showed that the correlation coefficients reached significance around the middle of the
311 double stance phase for all participants in normal and slow walking. Correlations were close to

312 zero at the beginning and at the end of the double stance phase, suggesting that preemptive, early
313 and late push-off did not influence foot placement errors.
314
315 [Figure 4 goes here]
316
317   The ankle moments during the double stance were correlated with foot placement errors at
318 heel strike in normal and slow walking (peak mean correlations over participants up to 0.39 and
319 0.37, respectively; see Fig. 4c). Correlations with ankle moments were also highest in the middle
320 of the double stance phase and were positive in the beginning of the double stance phase. The
321 significance of such correlation coefficients for all 30 participants was presented in Supplemental
322 Figure S4, which showed that the correlation coefficients reached significance around the middle
323 of the double stance phase for all except two participants in slow walking (participant 14 and
324 35). The correlations during the double stance phase for participant 28 were negative, opposite to
325 what we expected (Fig. 4c and Supplemental Figure S4).
326
327 [Figure 5 goes here]
328
329   In line with the correlations, all the kinetic time series during the double stance phase were
330 larger for "most positive" foot placement errors than for "most negative" foot placement errors in
331 both walking conditions (Figs. 5a-c). As shown in Figures. 5a-c, the combined AP GRF was
332 higher in the first half and lower in the end of the double stance phase for "most positive" foot
333 placement errors; the trailing leg's AP GRF and ankle moment were higher in the middle of the
334 double stance phase for "most positive" foot placement errors. The differences of all three
335 kinetic time series between "most positive" and "most negative" foot placement errors in both
336 normal and slow walking reached significance in the majority of the double stance phase, see
337 Supplemental Figure S5.
338

Discussion

340 We sought to test the hypothesis that humans employ ankle push-off control to compensate for
341 errors in AP foot placement during steady-state walking. Our correlations between the foot
342 placement errors at heel strike and all three kinetic time series during the subsequent double
343 stance phase appear to confirm this. This does not come as a surprise, as several modeling
344 studies demonstrated the capacity of ankle push-off modulations in improving robustness against
345 perturbations (Hobbelen & Wisse, 2008; Kim & Collins, 2013, 2017; Stephens & Atkeson,
346 2009). Moreover, correlations between push-off modulations and deviations in CoM trajectories
347 from AP perturbations have already been found in perturbed human walking (Afschrift et al.,
348 2021; Rafiee & Kiemel, 2020; van Mierlo et al., 2021; Vlutters et al., 2016). Such correlations
349 arguably arise from feedback mechanisms. Recently, van Leeuwen et al. (2021) reported that
350 errors in medio-lateral foot placement were corrected by ankle moments during the subsequent
351 stance phase. We here supplemented these findings by showing evidence for a push-off

352 mechanism used to correct for errors in foot placement during steady-state walking in the AP
353 direction.
354   In steady-state normal walking, among the three investigated kinetic time series, we found the
355 largest peak (over the stride cycle) of the mean correlations (across all participants) to be the one
356 between foot placement errors and trailing leg's AP GRF (up to 0.45), followed by (peak)
357 correlations between the foot placement errors and trailing leg's ankle moment (up to 0.39), and
358 the (peak) correlations between the foot placement errors and combined AP GRF (up to 0.34).
359 Feedback control based on foot placement error may primarily serve for control of the push-off
360 force from the trailing leg, which is strongly determined by the ankle moment. Push-off can be
361 generated by ankle, knee, and hip muscles (Kuo, 2002). At the instant of maximal trailing leg
362 power, the gain from the ankle moment to the trailing leg's AP GRF is ten times larger than the
363 gain from the hip joint moment (Toney & Chang, 2016). It is therefore not unexpected that
364 correlations for the ankle moment are close to the correlations for the trailing leg's AP GRF.
365   Peaks in the correlations between foot placement errors and kinetic variables occurred around
366 the middle of the subsequent double stance phase (Figs. 4a-c), while the peak combined/trailing
367 leg's AP GRF and the peak trailing leg's ankle moment all occurred already in the beginning of
368 the subsequent double stance phase (Fig. 5). Both observations imply that modulations of the
369 CoM states are less prevalent during the peak combined/trailing leg's AP GRF or peak ankle
370 moment, but mostly around the middle of the double stance phase, at which time the CoM AP
371 velocity and ankle power is highest (Hernández et al., 2009; Kuhman & Hurt, 2019; Lipfert et
372 al., 2014). Modulations of the CoM states may be achieved either by adjusting the trailing leg's
373 AP GRF and ankle moment magnitude (e.g., Fig. 5c), or by modulating their timings (duration of
374 the double stance phase and relative duration of particular force/torque in the double stance
375 phase) (Kuhman & Hurt, 2019; Toney & Chang, 2016; van Mierlo et al., 2021; Williams &
376 Martin, 2019). For instance, in slow walking the peak in combined AP GRF occurs later in too
377 large foot placement error steps than in too small foot placement error steps (Fig. 5b), which may
378 imply a prolonged activation of the muscles contributing to this force. Yet, the prolonged
379 activation mechanism in slow walking cannot be directly verified or falsified from Figures 4 and
380 5 due to the normalization of the double stance phase to a fixed window. The time delay between
381 heel strike and the peak in the correlations between foot placement errors and ankle moment in
382 normal walking was about 80 ms. Feedback delay in control of human ankle moments is
383 arguably longer ($\approx$ 100 ms) due to signal transmission, sensory integration in the nervous
384 system and the electromechanical delay (Afschrift et al., 2021; Welch & Ting, 2008). Rather
385 than directly using foot placement error at heel strike, humans might predict their foot placement
386 error shortly before heel strike as input for the (ankle) push-off modulation. The correlations
387 between the CoM states and the AP foot placement shortly before heel strike were close to the
388 ones at heel strike (Fig. 2). This implies a largely similar foot placement accuracy when
389 predicted prior to or at foot placement. Whether and how humans estimate foot placement error
390 around foot placement, however, requires further investigation.

391   The positive correlations between foot placement errors and ankle moment at initial double
392   stance phase in normal speed (Fig. 4c) suggest limited ankle push-off modulations before
393   contralateral heel strike. The correlations for ankle moment were positive throughout the double
394   stance phase except at the end, and peak correlations did not appear until the middle of the
395   double stance phase (Fig. 4c). Our findings are consistent with the study by Kuhman & Hurt,
396   (2019) who found that at human preferred steady-state walking speed (around 1.4 m/s), the peak
397   trailing leg's AP GRF, the onset and peak of trailing leg power and the peak ankle power all
398   occurred after contralateral heel strike. Humans seemingly rely less on the more energy efficient
399   preemptive push-off strategy to stabilize gait than suggested by modeling studies (Kuo, 2002;
400   Ruina et al., 2005). Potentially, they opt for producing push-off somewhat later to incorporate
401   sensory input information about foot placement error.
402   We showed that steady-state walking relies on more or less the same push-off strategy as
403   perturbed walking, where a forward push led to more forward foot placement (Vlutters et al.,
404   2018b), followed by CoP modulation (shorter double stance duration and longer CoP distance
405   travelled, see van Mierlo et al., 2021) from either weight shift of the leading leg (Hof, 2007) or
406   plantarflexion ankle moment modulations (Gruben & Boehm, 2014; Vlutters et al., 2018b),
407   contributing to a reduction of the CoM AP velocity over the double stance phase. Van Mierlo et
408   al. (2021) found CoP modulation to be absent for backward perturbations, presumably because
409   adjustments in foot placement sufficiently reduced the foot placement error (see Fig. 5 from
410   Vlutters et al., 2018b). According to Vlutters et al., (2018a), changing magnitude and direction of
411   AP perturbations on the pelvis near foot contact hardly affected the AP foot placement in both
412   the first and second recovery step. This suggests that a limited response time for foot placement
413   modulation primarily calls for push-off modulation. Apparently, humans cope with perturbations
414   by complementing foot placement with push-off control to correct the remaining foot placement
415   errors.
416   Older adults have poorer foot placement accuracy, at least in the medio-lateral direction
417   (Arvin et al., 2018). They have a reduced ankle push-off power generation (Franz, 2016;
418   Hernández et al., 2009). One may therefore expect the older adults have poorer gait robustness
419   due to larger foot placement errors and a reduced capacity to correct for these. Future work
420   should compare age-related differences in foot placement error at the beginning and the end of
421   the double stance phase and relate them to differences in push-off modulation. This can further
422   clarify gait adaptations in the elderly, such as the distal-to-proximal redistribution of push-off
423   power production (Franz, 2016).
424   We interpreted the modulation of the push-off force by the trailing leg in terms of gait
425   stability. Admittedly, the modulation of push-off force might also be explained by speed
426   regulation. On a treadmill, speed is controlled from step to step and may results in an over-
427   correction of speed errors with respect to the treadmill speed (Dingwell & Cusumano, 2015).
428   When walking at different steady-state speeds, humans can adjust the relative duration of the
429   double stance phase (cf. the percentage for normal and slow walking in Fig. 4), which may lead
430   to changes in magnitudes of AP GRF (Williams & Martin, 2019). Here, we also observed over-

431 correction of foot placement errors by the combined AP GRF at the subsequent step (see the end
432 of the stride cycle in Fig. 4a and Fig. 5a). The foot placement error is determined by two
433 variables: CoM states and foot placement at heel strike. For an inverted pendulum model
434 walking at a nominal speed, perturbations leading to positive foot placement errors reduced
435 walking speed and perturbations leading to negative foot placement errors increased walking
436 speed (Hof, 2008). Corrections of foot placement errors probably also correct speed errors with
437 respect to the treadmill. Our current data do not allow for directly distinguishing whether
438 maintaining gait stability or constant speed were the *primary* control goal. Either way, it is likely
439 to be an improper dichotomy given their interdependence (Hof, 2008).
440   Our study suggests that push-off control corrects foot placement errors in steady-state
441 walking. Push-off, however, also contributes to the leg swing (Zelik & Adamczyk, 2016) and to
442 the foot trajectory in the early swing phase. This is evident from humans' responses to stepping
443 target perturbations (Barton et al., 2019). Contrary to push-off control, swing leg control for foot
444 placement is largely passive except at the beginning and end of the swing phase, as indicated by
445 quick bursts of leg swing and retraction impulses (Doke et al., 2005). This passive
446 ("predictable") pendular dynamics in the swing phase may hence be exploited by the
447 feedforward/anticipative control of push-off for the desired foot placement. It is currently
448 unknown whether in steady-state walking feedforward control of push-off is also used. However,
449 our findings seemed to disagree with the assumption of feedforward control of push-off
450 determining the next foot placement. This can be seen from the fact that 1) the correlations
451 between the foot placement errors and the combined AP GRF at foot placement were close to
452 zero (Fig. 4a), 2) the correlations between the foot placement errors and the trailing leg's AP
453 GRF at the beginning of the subsequent double stance phase were close to zero (Fig. 4b), and 3)
454 the foot placement errors were over-corrected by the combined AP GRF after the subsequent
455 double stance phase (Fig. 4a and 5a). To further unravel the stabilizing mechanisms of push-off
456 control, modeling approaches can elucidate when implementing feedforward and/or feedback
457 push-off controllers based on foot placement errors for simple bipedal walkers under noisy
458 conditions. Ryu & Kuo (2021) showed pure feedback and pure feedforward control to be
459 susceptible to sensor noise and process noise (e.g., uncertainty in the environment), respectively,
460 and the combined feedforward and feedback controller was best for stable and robust walking.
461   **Limitations**. Our study comes with several limitations. Before listing them, however, we
462 want to repeat our statement-of-warning, namely, that the correlations we observed should be
463 interpreted with care. Next to feedback control there might be other sources causing them, such
464 as passive dynamics (Patil et al., 2019). Future studies may employ (perceptual or mechanical)
465 perturbations (Fettrow et al., 2019; Roden-Reynolds et al., 2015) and/or EMG responses (Rankin
466 et al., 2014; van Leeuwen et al., 2021; Vlutters et al., 2019) to disentangle contributions from
467 feedback control and from passive dynamics.
468   We did not apply any normalization, to render our variables of interest easier to interpret.
469 Admittedly, normalization can reduce inter-participant variability. For this, however, we
470 customized each participant's treadmill speed, i.e., we maintained constant dimensionless speeds

471 (Hof, 1996). Although this is a valid approach to account for participants' leg differences,
472 controlling speeds and additionally stride frequency by metronome may increase the difficulty of
473 the walking task compared to (unconstrained) natural walking.
474   We observed an outlier with large negative correlations for the ankle moments only in slow
475 walking in Figure 4c. This participant's right ankle moments were negatively correlated to (left)
476 foot placement errors, and the foot placement of the right leg was consistently further forward
477 than of the left leg. We suspect this participant used a different and uncommon walking strategy
478 in slow walking. And there was another participant that might be considered an outlier when
479 considering the correlations between the left trailing leg's AP GRF and right foot placement
480 errors in slow walking in Figure 4b. However, this participant showed different behavior only
481 prior to heel strike.
482

483 ## Conclusion

484 We correlated foot placement errors with kinetic time series of ankle push-off to test the idea that
485 foot placement errors are corrected for by push-off in steady-state walking. We found ankle
486 push-off torque to be correlated to AP foot placement errors mainly around the middle of the
487 double stance phase both in steady-state normal and slow walking, confirming our hypothesis
488 that humans employ ankle push-off control to compensate for errors in AP foot placement during
489 steady-state walking.
490

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667

Figure 1

Illustration of positive and negative foot placement errors.

For certain CoM states (CoM AP position and velocity at heel strike), a too large step yields a positive foot placement error, while a too small step leads to a negative foot placement error. A vanishing foot placement error implies linear predictions of foot placement from CoM states.

CoM states

positive foot
placement error

negative foot
placement error

zero foot placement error:
$FP = \beta_{pos} \cdot CoM_{pos} + \beta_{vel} \cdot CoM_{vel}$
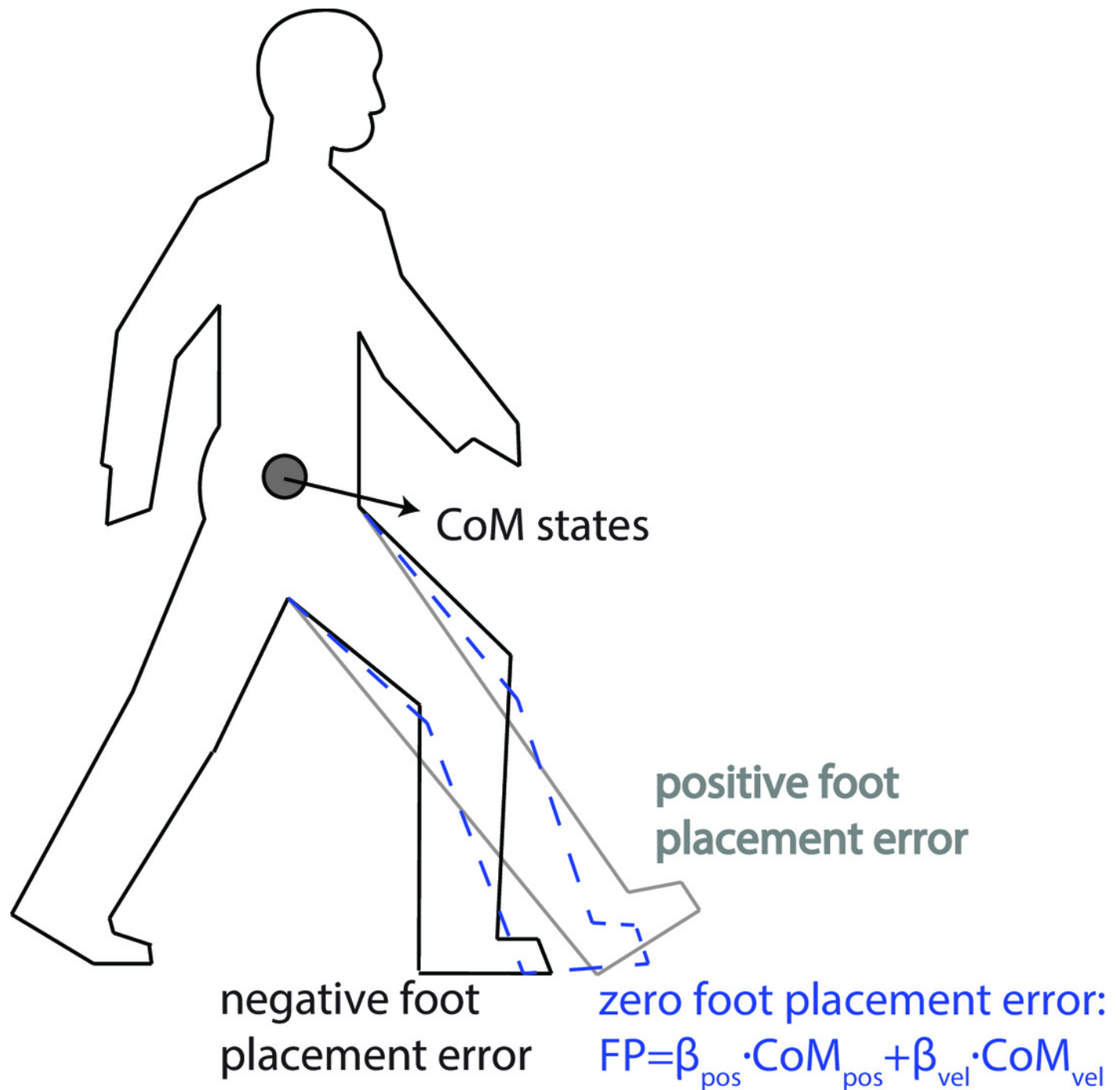
Figure 2

Proportion of foot placement variance explained by CoM states, for normal (a) and slow walking (b).

Every curve represents the explained variance for a participant. The dashed vertical lines correspond to foot placement, and the phases after heel strike correspond to the double stance phase.
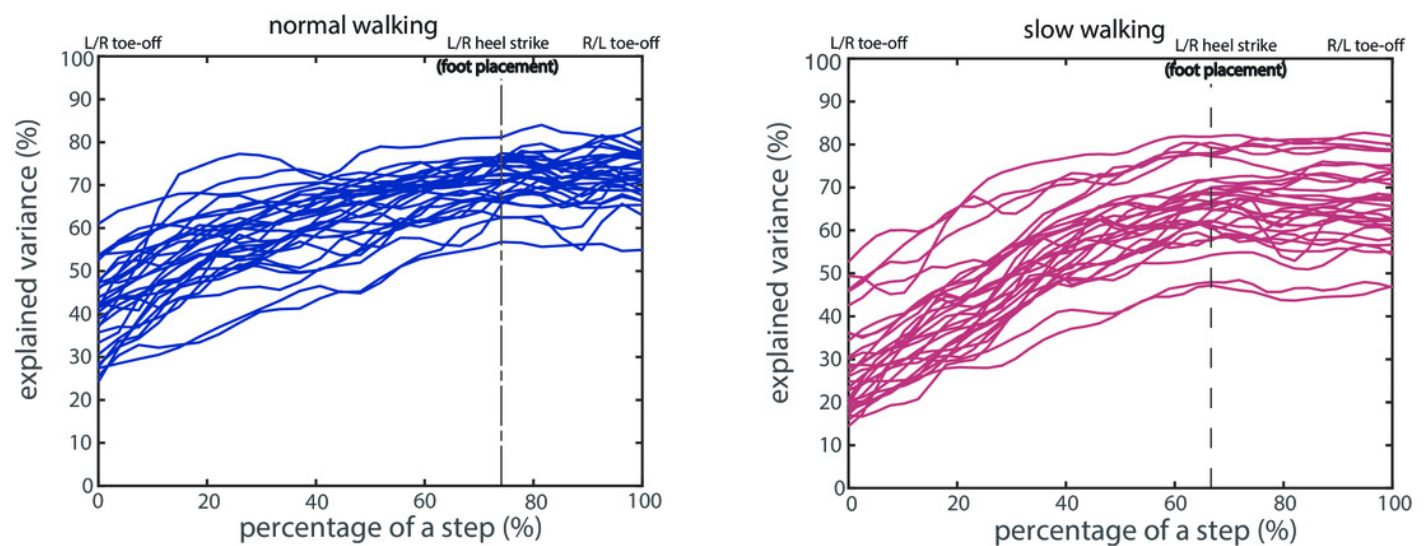
Figure 3

Distributions of foot placement errors.

(a) Distributions of foot placement errors for normal and slow walking for all participants. Gaussian distributions are fitted to the data in two conditions. (b) The group mean values of the averaged 10 most positive and 10 most negative foot placement errors per participant. Error bars indicate the standard deviation across participants.
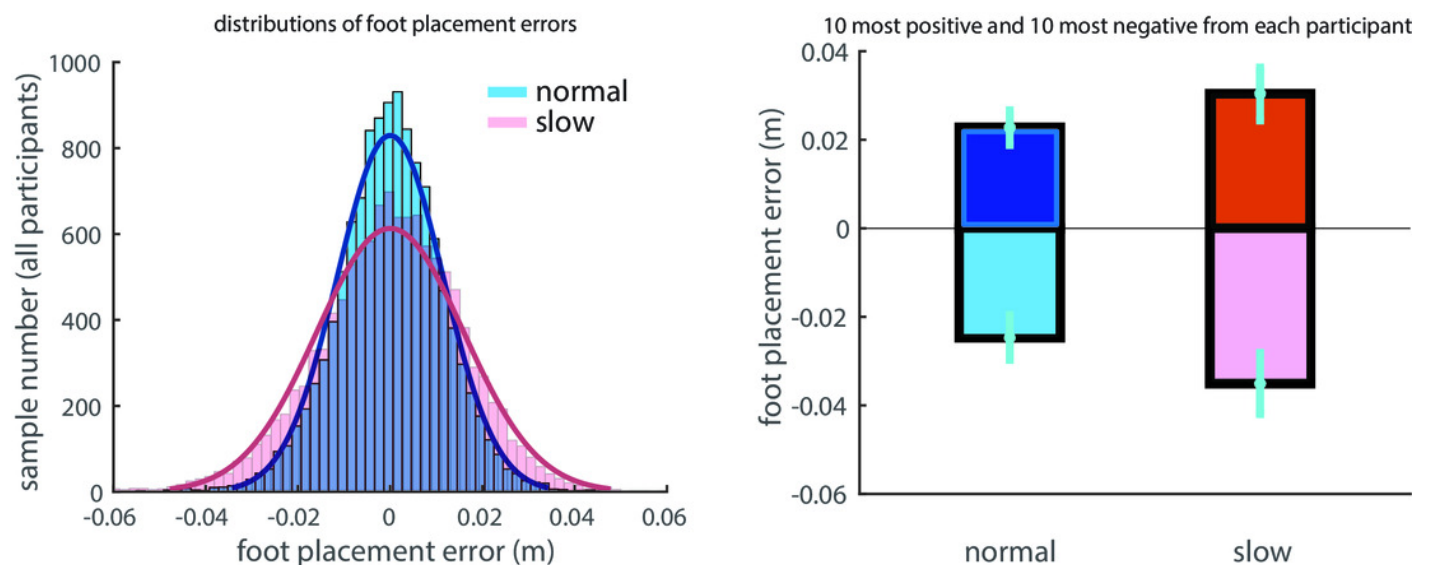
Figure 4

Correlations between foot placement errors at heel strike (left dash-dotted and dashed lines) and different kinetic time series in normal and slow walking.

(a) Combined AP GRF; (b) Trailing leg's AP GRF; (c) Ankle moment. The thin curves are correlations per participant and per foot, the thick ones are means over participants. The phases between the dash-dotted lines or the dashed lines correspond to the double stance phase in normal and slow walking, respectively. Note that the trailing leg's AP GRF and ankle moment were zero during the swing phases at the end of the stride cycle, thus the correlations were not shown.
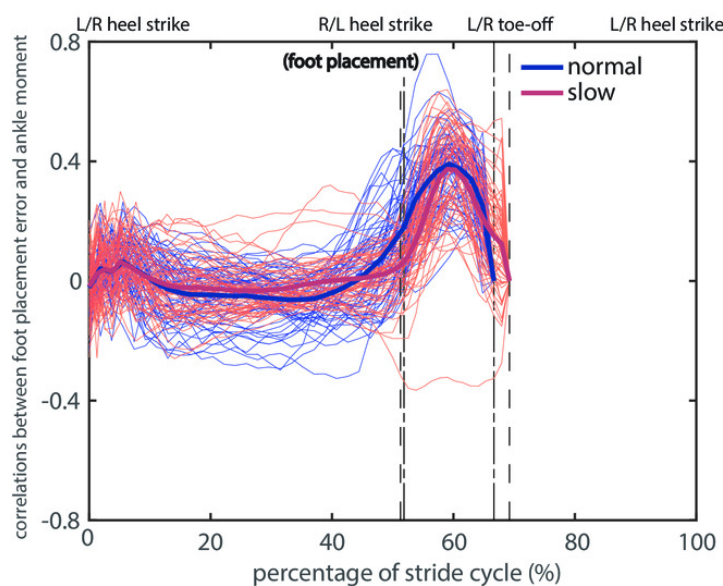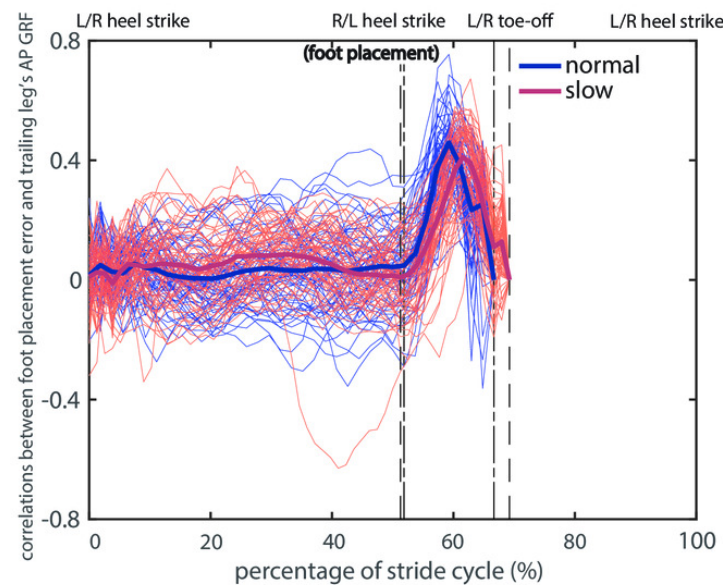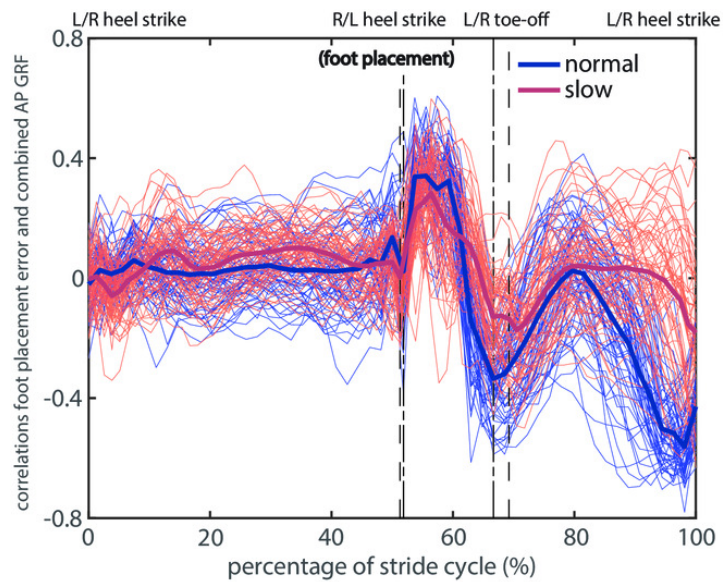
Figure 5

Averaged kinetic time series corresponding to the "most positive" and "most negative" foot placement errors in normal and slow walking.

(a) Combined AP GRF; (b) Trailing leg's AP GRF; (c) Ankle moment. The phases between the dash-dotted lines or the dashed lines correspond to the double stance phase in normal and slow walking, respectively.