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American Society of Biomechanics Journal of Biomechanics Award 2018: Adaptive motor planning of center-of-mass trajectory during goal-directed walking in novel environments

Mary A. Bucklin [a,b,*], Mengnan/Mary Wu [a], Geoffrey Brown [a], Keith E. Gordon [a,c]

[a] *Department of Physical Therapy and Human Movement Sciences, Feinberg School of Medicine, Northwestern University, Chicago, IL, USA*
[b] *Department of Biomedical Engineering, Northwestern University, Evanston, IL, USA*
[c] *Research Service, Edward Hines Jr. VA Hospital, Hines, IL, USA*

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ABSTRACT

To aid in the successful execution of goal-directed walking (discrete movement from a start location to an end target) the central nervous system forms a predictive motor plan. For the motor plan to be effective, it must be adapted in response to environmental changes. Despite motor planning being inherent to goal-directed walking, it is not understood how the nervous system adapts these plans to interact with changing environments. Our objective was to understand how people adapt motor plans of center of mass (COM) trajectory during goal-directed walking in response to a consistent change in environmental dynamics. Participants preformed a series of goal-directed walking trials in a novel environment created by a cable robot that applied a lateral force field to their COM. We hypothesized that participants would adapt to the environment by forming an internal model of their COM trajectory within the force field. Our findings support this hypothesis. Initially, we found COM trajectory significantly deviated in the same direction as the applied field, relative to baseline (no field) ($p = 0.002$). However, with practice in the field, COM trajectory adapted back to the baseline ($p = 0.6$). When we unexpectedly removed the field, participants demonstrated after-effects, COM trajectory deviated in the direction opposite of the field relative to baseline ($p < 0.001$). Our findings suggest that when performing a goal-directed walking task, people adapt a motor plan that predicts the COM trajectory that will emerge from the interaction between a specific set of motor commands and the external environment.

1. Introduction

Goal-directed walking - the initiation, execution and termination of discrete walking bouts intended to move the body to a desired location – is a frequent activity of daily living (Bienkiewicz et al., 2014; Mlinac and Feng, 2016). Before initiating a goal-directed walking movement, the central nervous system forms a motor plan (Glover, 2004; Patla et al., 1999; Woodworth, 1899), a set of motor commands that are predicted to accomplish task-specific goals. To be effective, motor plans must be continually updated to accomodate changes in external (environmental) and internal (body) dynamics (Shadmehr and Mussa-Ivaldi, 2012). Despite motor planning being an inherent part of goal-directed walking, it is not well understood how the nervous system adapts these plans to interact with changing dynamics (Babic et al., 2016).

During goal-directed walking the nervous system plans a desired center of mass (COM) trajectory (Hicheur et al., 2005; Lyon and Day, 1997; Vieilledent et al., 2001; Welch and Ting, 2008). This is illustrated by research examining gait patterns as participants navigated to and through a doorway (Hicheur et al., 2007). The authors found kinematic-invariant features of COM dynamics, including highly stereotypical trajectories and velocity profiles, in comparison to step-by-step foot placements, which varied within and across subjects. These past experiments provide insight about the planning of goal-directed walking in a known environment. However, adaptive planning of COM trajectory during goal-directed walking in changing environments has not been thoroughly investigated.

There is considerable research investigating how the nervous system adapts motor planning of hand trajectories in response to

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Abbreviations: COM, center-of-mass; APA, anticipatory postural adjustment.

[*] Corresponding author at: Feinberg School of Medicine, Northwestern University, Physical Therapy and Human Movement Sciences, 645 N. Michigan Ave, Suite 1100, Chicago, IL 60611, USA.

E-mail address: marybucklin2016@u.northwestern.edu (M.A. Bucklin).

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novel environmental dynamics created by robotic force fields (Franklin and Wolpert, 2011; Kawato, 1999; Shadmehr and Mussa-Ivaldi, 2012). People utilize variable control strategies to adapt upper-limb reaching movements. In consistent environments, people use an internal model – a relatively energetically efficient control strategy that is specifically tuned to the anticipated environment but may result in movement errors if unanticipated perturbations occur (Shadmehr and Mussa-Ivaldi, 2012; Wolpert et al., 1995). Alternatively, when reaching in an varying environment, people utilize high impedance strategies – a robust generalized resistance to external disturbances (Burdet et al., 2001; Osu et al., 2003; Takahashi et al., 2001) that typically requires greater energy consumption (Franklin et al., 2004). Hence, the nervous system can adapt different control strategies depending on priorities (e.g. error tolerance, energy) associated with task-specific goals (Todorov, 2004).

Evidence from motor control studies (Pham and Hicheur, 2009; Pham et al., 2007), and evolutionary hypotheses (Georgopoulos and Grillner, 1989; Grillner et al., 2008) suggest that goal-directed walking and reaching utilize a similar control framework for motor planning. However, there are task demands unique to walking, such as bipedal coordination, high injury risk (falling) and substantial metabolic requirements, which may influence the nervous system's priorities. For example, individuals with balance deficits may select wider steps (Aboutorabi et al., 2016; Matsubara et al., 2015), a strategy that can improve stability (McAndrew Young and Dingwell, 2012) but requires greater energy consumption (Donelan et al., 2001, 2004). Thus, there is value in explicitly investigating adaptive motor planning of COM trajectory during goal-directed walking.

Our purpose was to investigate how people adapt motor plans of COM trajectory during goal-directed walking to a novel and consistent environment. We created this environment by applying a continuous, laterally-directed force field to the COM that was proportional in magnitude to forward walking velocity. We hypothesized that when performing a goal-directed walking task in the novel and consistent force field, people would adapt by forming an internal model of their COM trajectory within the new environment (Shadmehr and Mussa-Ivaldi, 1994).

2. Methods

2.1. Participants

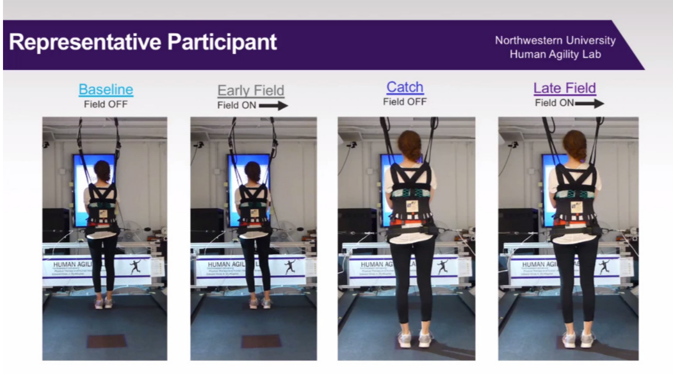
Thirteen healthy young-adults (7 females, 22.8 ± 2.1 years and 65.9 ± 8.5 kg, mean ± SD) participated. The Northwestern University Institutional Review Board approved the protocol and all participants provided informed written consent. Participants were able to walk continuously for 30 min without undue fatigue or health risks and were free of any musculoskeletal and/or vestibular pathologies affecting gait or balance.

2.2. Experimental setup

Participants preformed two blocks of 110 discrete goal-directed walking trials, walking from a start target to an end target (Fig. 1a). During each block, forces were directed either towards the participant's right or left side. Block order was randomized across participants. Post hoc testing revealed no effect of order (Supplementary methods). For simplicity and clarity, here we present only the block of trials when the force field was directed to the right.

Start and end targets (0.3 × 0.3 m square) were projected (Hitachi America, Ltd) on the floor (Fig. 1a). Target distance was adjusted for each participant to be 1.5x leg length, approximately a two-step task. For safety, participants wore a trunk harness attached to a passive overhead support (Aretech, Ashburn, VA) that did not provide bodyweight support or restrict movement.

To create a novel environment, a cable robot applied a lateral force field to the COM during walking (Fig. 1a) (Brown et al., 2017). The force field was proportional in magnitude to forward walking velocity and directed towards participant's right side (Fig. 1b). Real-time forward walking velocity was calculated using the derivative of position measured by a string potentiometer. Position data was sampled at 100 Hz, and low pass filtered to reject noise spikes in the derivative (velocity). Participants could not detect if the field would be applied until they began each trial and their forward velocity exceeded 0.2 m/s. The force field gain (80 N/(m/s)) was consistent across participants and selected to be challenging, but not strong enough to evoke a fall (Supplementary video). Maximum peak force applied per trial across all participants was 120.8 ± 7.8 N for force field trials.



To ensure similar forward walking velocities across all trials, participants received feedback each trial and were instructed to modify their next trial accordingly. A monitor provided visual feedback stating "too slow", "too fast", or "success", depending on how peak forward velocity compared to a desired value of 1.2 ± 0.1 m/s.

We placed 13 active markers on the pelvis and bilaterally on the greater trochanter, lateral malleolus, calcaneus, and 2nd and 5th metatarsals to measure kinematics. A 12-camera motion capture system (Qualisys, Gothenburg Sweden) recorded 3D marker coordinates at 200 Hz.

2.3. Protocol

Participants performed 110 consecutive goal-directed walking trials (Fig. 1c), consisting of 20 Baseline trials (no applied forces), followed by 70 Force Field trials, and concluding with 20 Washout trials (no applied forces). Additionally, three catch trials (no applied forces) were interspersed within the Force Field trials occurring during trial numbers 45, 60, and 75. Catch trials were used to evaluate control strategies. Participants were not aware of trial order.

Each trial began with the participant standing stationary with both feet located in the start target (Supplementary video). Next, participants heard an auditory "3-2-1" countdown followed by a "GO" cue. At the cue, participants walked to the end target. Participants always stepped first with their right foot. The trial concluded when both feet were located within the end target. A "beep" signalled trial completion. Participants then returned to the start target (no force fields were applied during this time). To minimize upper limb movements, participants crossed their arms. Besides these provisions, participants were told to complete the task in the manner they felt most comfortable.

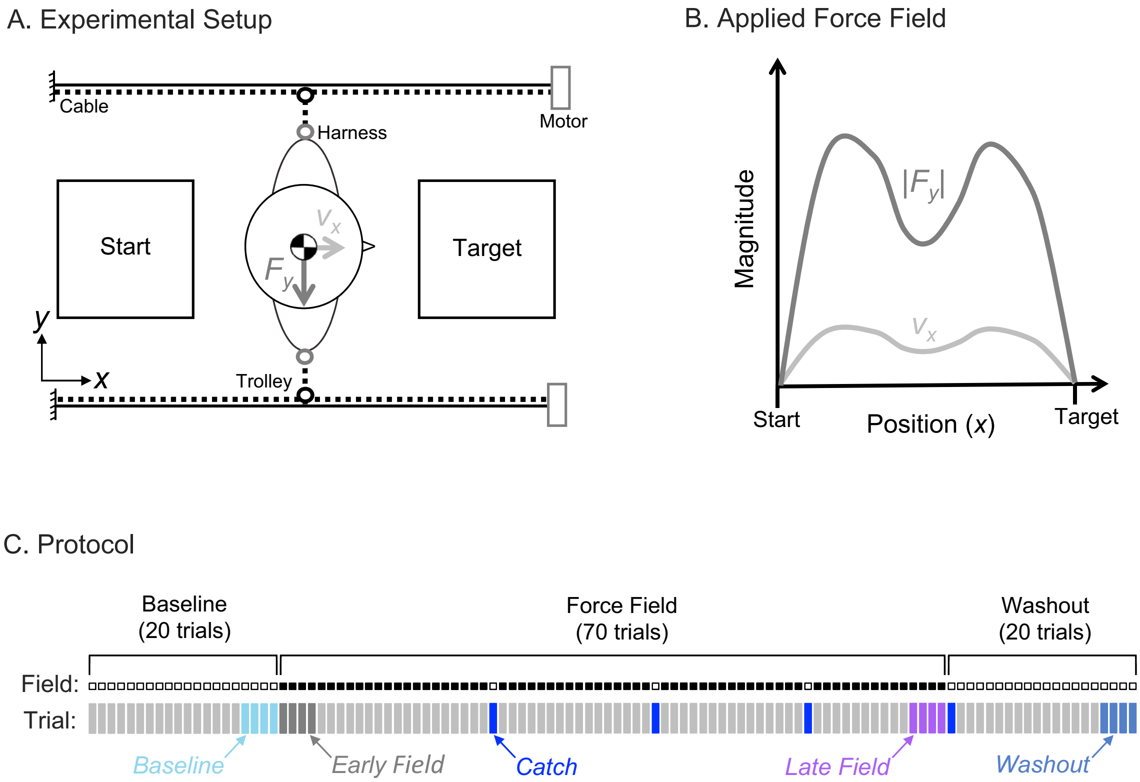


Fig. 1. Methods: (A) Experimental Setup, (B) Applied Force Field, and (C) Protocol. (A) Schematic top view of a participant shown performing the goal-directed walking task, walking from the start to the end target. The cable robot consisted of a pair of actuated cables (dashed black lines), routed through a trolley system (black circles), and attached bilaterally (grey circles) on the medial aspect of a snug pelvic harness worn by the participant. Force on each cable was controlled by a series-elastic linear motor (grey boxes). F_y (dark grey vector) represents force applied to the COM and v_x (light grey vector) represents forward walking velocity. (B) Representation of the force applied to the participant's COM during a force field trial. Force applied (dark grey trace) is proportional in magnitude to forward walking velocity (light grey trace) with a gain of 80 N/(m/s). (C) Participants performed 110 consecutive trials, each represented as a rectangular block ordered left to right. The force field was applied (black squares) during Force Field trials (except for catch trials) and absent (white squares) during Baseline and Washout trials. Data was analyzed during five distinct experimental four-trial periods highlighted in their respective colors. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.4. Data processing and calculations

Kinematic marker data was processed using Visual3D (C-Motion, Germantown, MD) and a custom MATLAB (MathWorks, Natick, MA) program. Marker data was gap-filled and low-pass filtered (Butterworth, 6 Hz cut-off frequency). Gait events, time of initial foot contact and toe-off, were identified by the inferior-superior positions of markers. Initial contact was identified as the local minimum of the calcaneal marker and toe-off as the local minimum of the 2nd metatarsal. All steps were visually inspected to verify accurate event detection. COM position was calculated in Visual3D as the center of the pelvis model, determined by three pelvic and two greater trochanter markers.

To characterize control of COM trajectory, we analyzed kinematic data of COM trajectory between start and end targets. We calculated **COM signed deviation**, the signed area of COM trajectory relative to a straight-line path originating from the lateral COM position at first toe-off (Fig. 2). **COM signed deviation** reflects directional biases in COM trajectory by taking the difference between areas on either side of a straight-line path.

To gain insight into the strategies that participants used to create the observed COM trajectory, we evaluated anticipatory postural adjustments (APA's) (McIlroy and Maki, 1993; Rueckert et al., 2016) by quantifying the lateral movement of the COM prior to forward movement. We calculated **COM lateral offset** as the lateral distance between the COM position at the "GO" cue, and the COM position at first toe-off (Fig. 2). Additionally, we evaluated foot placement using **step width**, calculated as the medio-lateral distance between the left and right 5th metatarsal markers at initial foot contact. We evaluated **step width** for the first two steps of each trial.

To estimate the rate participants adapted to the force field we calculated a **time constant** by fitting an exponential function (Patton et al., 2013) to **COM signed deviation** for each participant during the first 15 trials in the force field, prior to the first catch trial. **Time constants** were then averaged across participants to obtain a single adaptation rate value.

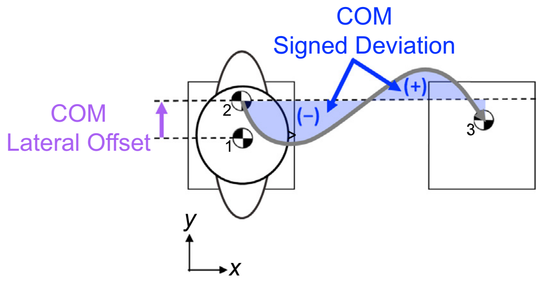


Fig. 2. Center of Mass Data Analysis. **COM lateral offset**, shown in purple, was defined as the lateral distance between the COM location before the "GO" cue (1) and COM location at first toe-off (2). This value represents lateral excursion of the COM prior to forward movement. The grey trajectory represents the COM motion during the trial. **COM signed deviation** was defined as the blue shaded area between the grey trajectory and a straight-line path originating from (2) and ending at (3). Deviations to the right of the straight-line path were given negative values, and deviations to the left were positive. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.5. Statistical analysis

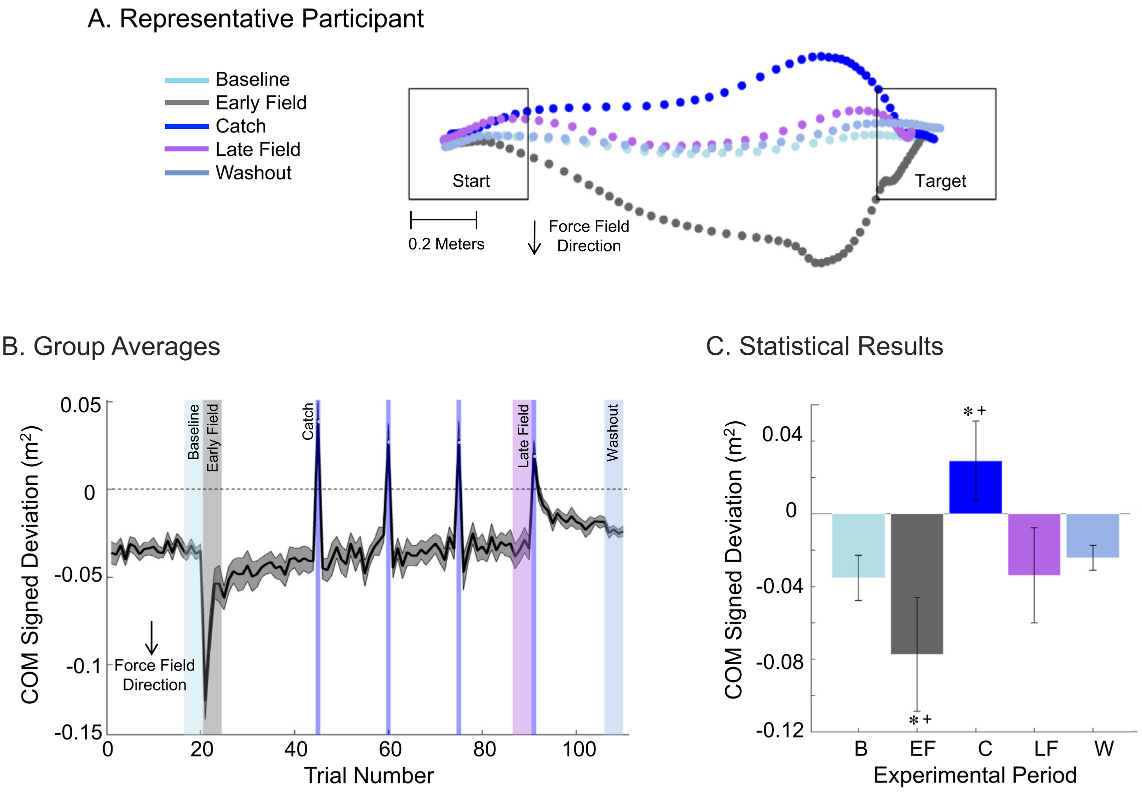
For statistical analysis, we averaged four trials at five different experimental periods defined within the 110 consecutive stepping trials (Fig. 1c). *Baseline* performance was estimated as an average of trials 17–20 (last four trials of Baseline), *early field* was an average of trials 21–24 (first four trials of Force Field), *late field* was an average of trials 87–90 (last four trials of Force Field), *catch* was an average of trials 45, 60, 75, and 91 (three catch trials and first trial of Washout) and finally *washout* was an average of trials 107–110 (last four trials of Washout). For each participant we calculated these average performance estimates for all five experimental periods (*baseline*, *early field*, *late field*, *catch*, and *washout*) for each metric (**COM signed deviation**, **COM lateral offset**, and **step width**).

All statistical analyses were conducted using SPSS (IBM, Armonk, NY). We implemented one-way repeated measures ANOVAs with a within subject factor of experimental period (*baseline*, *early field*, and *late field*, *catch*, and *washout*), to evaluate all metrics (**COM signed deviation**, **COM lateral offset**, and **step width**). For all statistical tests, if sphericity was violated, the Greenhouse-Geisser F-statistic and p-value were used to test the main effect. When a significant main effect was found, Bonferroni-corrected pairwise comparisons were made between experimental periods. Six pairwise comparisons were made (*baseline-early field*, *baseline-late field*, *baseline-catch*, *baseline-washout*, *early field-late field*, and *late field-catch*) to evaluate adaptation and control strategies. Significance was set at the $p < 0.05$ level for the ANOVAs and pairwise comparisons.

3. Results

3.1. COM signed deviation

There was a significant main effect of experimental period for **COM signed deviation** ($p < 0.001$). During the initial walking trials in the field, participants demonstrated a large lateral deviation of COM trajectory in the direction of the applied force field (Fig. 3) (Supplementary video). Negative **COM signed deviation** indicates that COM trajectory was biased toward the right. **COM signed deviation** changed from $-0.035 \pm 0.01\ \text{m}^2$ (mean ± SD) at *baseline* to $-0.077 \pm 0.03\ \text{m}^2$ at *early field*. Pairwise comparisons identified significant differences in **COM signed deviation** between *baseline* and *early field* ($p = 0.002$). As participants continued to perform walking trials in the force field, **COM signed deviation** returned to *baseline* values. Pairwise comparisons found no significant differences between *baseline* and *late field* ($p = 0.6$). Furthermore, there were significant differences between *early field* and *late field* ($p = 0.004$). **COM signed deviation** changed from $-0.077 \pm 0.03\ \text{m}^2$ at *early field* to $-0.034 \pm 0.02\ \text{m}^2$ at *late field*. During catch trials, participants displayed large lateral COM deviations in the opposite direction of the applied force field, $0.029 \pm 0.03\ \text{m}^2$. Pairwise comparisons identified significant differences in **COM signed deviation** between *baseline* and *catch* ($p < 0.001$) and between *late field* and *catch* ($p < 0.001$). Finally, when the force field was removed during washout, participants **COM signed deviation** trended towards *baseline* values. However, *washout*, $-0.024 \pm 0.01\ \text{m}^2$, was significantly different from *baseline* ($p = 0.008$).


A. Representative Participant

B. Group Averages

C. Statistical Results

Fig. 3. COM Signed Deviation (A) Representative Participant, (B) Group Averages, and (C) Statistical Results. (A) COM trajectory during select trials from analysis periods for a single representative participant. (B) Group averages of **COM signed deviation** are shown across experimental trial (black line with grey standard error shading). The background distinguishes trials used for data analysis periods, shaded in their respective colors. (C) Mean ± SD for **COM signed deviation** across experimental period. X-axis labels: B, EF, C, LF, and W represent periods listed in order in figure (A). Significance ($p < 0.05$) from *baseline* is denoted by (*) and signficance ($p < 0.05$) from *late field* is denoted by (+).

3.2. COM lateral offset

Statistical analysis revealed a main effect of experimental period in **COM lateral offset** ($p < 0.001$). During *early field* there was no change in **COM lateral offset** (Fig. 4) (Supplementary video). Pairwise comparisons found that **COM lateral offset** was not significantly different between *baseline* and *early field* ($p = 0.60$). As participants continued to perform walking trials in the field, **COM lateral offset** increased in the opposite direction of the applied force field. Positive **COM lateral offset** values indicate movement to the left. **COM lateral offset** changed from 0.014 ± 0.00 m at *baseline* to 0.027 ± 0.01 m at *late field*. This change in **COM lateral offset** was reflected in pairwise comparisons revealing a significant difference between *baseline* and *late field* ($p = 0.011$), as well as a significant difference between *early field* and *late field* ($p = 0.008$). No significant difference was found between *late field* and *catch* ($p = 0.27$). Additionally, a significant difference was found between *baseline* and *catch* ($p < 0.001$), with the *catch* values deviating in the same direction as the *late field* trials, relative to *baseline*. Finally, no significant difference was found between *baseline* and *washout* ($p = 0.60$).

3.3. Step width

Statistical analysis revealed a significant main effect of experimental condition for **step width** for both step one ($p < 0.001$) and two ($p < 0.001$). During *early field* trials participants took wide steps for both step one and two (Fig. 5) (Supplementary video). **Step width** increased from 0.13 ± 0.02 m at *baseline* to 0.24 ± 0.06 m at *early field* for step one and from 0.12 ± 0.02 m to 0.22 ± 0.08 m for step two. These adjustments were supported by pairwise comparisons revealing significant increases in **step width** between *baseline* and *early field* for step one ($p < 0.001$) and step two ($p = 0.001$). Across trials in the field, participants continued to take wide steps for both step one and step two. This is supported by a significant difference between *baseline* and *late field* for step one ($p < 0.001$) and step two ($p < 0.001$), as well as no significant difference between *early field* and *late field* for step one ($p = 0.6$) and step two ($p = 0.6$). When the force field was unexpectedly removed during catch trials, **step width** values immediately returned to *baseline* values. There were no significant differences between *baseline* and *catch* for step one ($p = 0.1$) or step two ($p = 0.6$), and there was a significant difference between *late field* and *catch* for step one ($p < 0.001$) and step two ($p = 0.001$). There was no significant difference between *baseline* and *washout* trials for step one ($p = 0.6$) or step two ($p = 0.6$).

3.4. Adaptation rate

The average **time constant** for all participants was 16 ± 11 trials based on the the **COM signed deviation** metric.

4. Discussion

This study investigated how people plan COM trajectory when a laterally-directed force field was applied to their COM during goal-directed walking. Initially, we observed significant changes in **COM signed deviation** in the same direction as the applied field. With practice **COM signed deviation** adapted back to *baseline* values. During catch trials, when the force field was unexpectedly removed, we observed after-effects, demonstrated by a significant change in **COM signed deviation** in the direction opposite of the force field. These findings support our hypothesis that when performing a goal-directed walking task in a novel and consistent force field, people form an internal model that predicts the COM trajectory that will emerge from the interaction between a specific set of motor commands and the external environment.

4.1. COM adaptation

When the force field was first unexpectedly applied (*early field*) all participants demonstrated a change in **COM signed deviation** in the same direction as the field, indicating that the applied forces were strong enough to alter normal COM movement (Fig. 3). With practice, participants adapted their COM trajectory, resulting in no difference between **COM signed deviation** during *late field* and *baseline*. Our findings suggests that a control objective of the nervous system during goal-directed walking may be to produce a

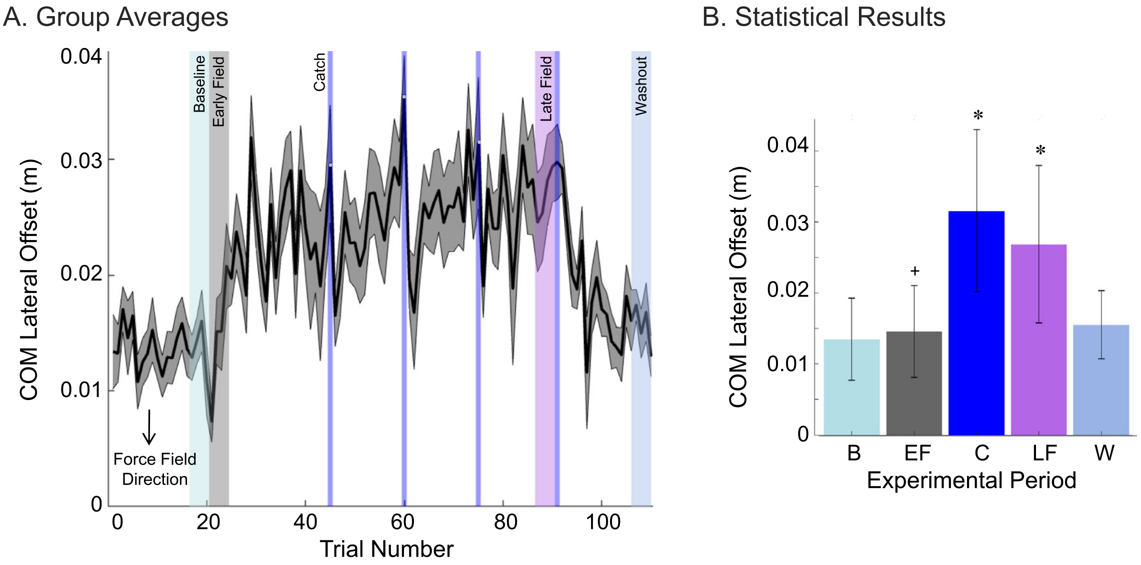


Fig. 4. COM Lateral Offset (A) Group Averages and (B) Statistical Results. (A) Group averages of **COM lateral offset** are shown across experimental trials (black line with grey standard error shading). The background distinguishes trials used for data analysis periods, shaded in their respective colors. **COM lateral offset** did not immediately change when the field was first turned on, but adapted to an increased value with practice in the field. (B) Mean ± SD for **COM lateral offset** across experimental period. X-axis labels: B, EF, C, LF, and W represent periods listed in order in figure (A). Signifiance ($p < 0.05$) from *baseline* is denoted by (*) and signficance ($p < 0.05$) from *late field* is denoted by (+).

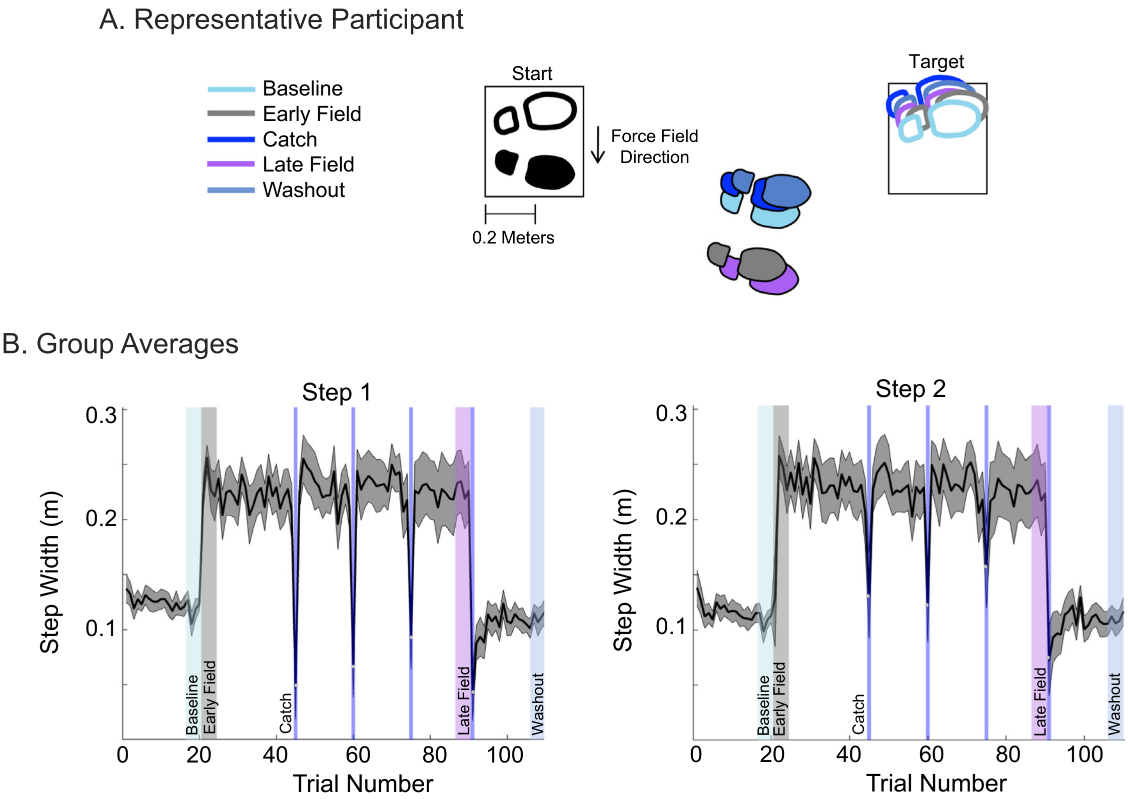


Fig. 5. Step Width (A) Representative Participant and (B) Group Averages. (A) Foot placement during select trials from analysis periods for a single representative participant. Filled in foot prints represent the right foot and outlined foot prints represent the left foot. Black and white foot prints show feet at start position and colored foot prints show step one and step two, respectively. (B) Group-averaged **step width** across experimental trials (black line with grey standard error shading) shown for step one (left graph) and step two (right graph). The background distinguishes trials used for data analysis periods, shaded in their respective colors. **Step width** for both step one and step two increased within the first trial in the field and did not adapt back to baseline after practicing in the field. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

desired kinematic trajectory. This is consistent with previous studies that observed stereotypical COM trajectories during goal-directed walking (Hicheur et al., 2007).

In the current study, COM trajectory adapted within tens of trials. This is similar to previous adaptation rates found for walking variables such as limb dynamics (Emken and Reinkensmeyer, 2005; Reisman et al., 2005), as well as for COM trajectory during a squat-to-stand task (Babic et al., 2016). Yet, our results are fast relative to adaptation of hand trajectory that can require several hundreds of trials (Shadmehr and Mussa-Ivaldi, 2012). Given that adaptation rate is known to increase with force field magnitude (Patton, 2001), our adaptation rate may have been influenced by the relatively large magnitude force used to disrupt normal whole-body movement. Walking-specific factors may have also played a role. For example, people may select strategies that minimize risk (Sanger, 2014). As such, high risk of injury (e.g. falls) may encourage more rapid adaptation during walking.

Body mass may have influenced **COM signed deviation** between participants. In a host-hoc analysis, we found a significant linear regression relationship ($p = 0.043$) with an R^2 value of 0.348 between body mass and **COM signed deviation** during the first trial of Force Field. Potentially, the differences in magnitude of **COM signed deviation** may have influenced learning mechanisms. Additionally, limb dominance may have also influenced **COM signed deviation** between participants. However, given that 10 of the 13 participants were right-limb dominant, we were unable to explicitly evaluate the influence of limb dominance.

4.2. COM internal model formation

During catch trials, **COM signed deviation** increased in the direction opposite of the force field (Fig. 3). The observation of this after-effect supports our hypothesis that participants would form an internal model that accomodates the external environment. This is comparable to reaching studies (Shadmehr and Mussa-Ivaldi, 1994, 2012), which also observed that participants formed internal models of hand trajectory when reaching amid a conistent force field. Our findings suggest that the nervous system plans motor commands specifically tuned to the anticipated environment. We believe that this strategy may be benefical for enhancing walking specific factors such as energy efficiency (Srinivasan and Ruina, 2006), walking speed (Gilchrist, 1998), and maneuverability (Acasio, 2016). However, such a strategy may also be risky because is it prone to errors when unanticipated environmental changes occur. Alternatively, participants could have utilized a more robust, high impedance strategy (Franklin et al., 2003), e.g. by increasing muscle co-contraction to resist unanticipated change. However, such a stratagy would likely increase energy requirements (Franklin et al., 2004). Thus, an internal model may be desirable in a consistent environment when the risk of an unanticipated change occurring is low.

Amid data analysis, we observed differences in **COM signed deviation** before and after catch trials. To further investigate this, we conducted a paired *t*-test comparing trials before (trials 44, 49, and 74), and after (trials 46, 61, and 76) catch. We found a significant difference (p = 0.008), with trials before catch being closer to *baseline*. Similar to previous studies investigating the influence of trial uncertainty (Scheidt et al., 2001), our finding shows that as a result of the uncertainty arising from the catch trial, the internal model reverts in the direction of *early adapt*.

4.3. Underlying control strategies

To understand the strategies underlying the resulting COM trajectory, we quantified **COM lateral offset**, a measure of APAs. Generally, APAs are thought to assist with balance control during step initiation (Jian et al., 1993). However, our results suggest a novel interpretation; APA's may also serve as an offset for a desired COM trajectory. In response to the force field directed toward the right, participants adapted an APA to the left. This lateral offset may aid in control of COM trajectory by biasing the participant's posture in anticipation of the external environment. This theory is supported by our finding that **COM signed deviation** returned to *baseline* with practice in the force field while **COM lateral offset** did not (Fig. 4). Collectively, our results support that **COM lateral offset** was an important strategy in controlling the COM trajectory.

To further understand the strategies underlying the resulting COM trajectory, we evaluated foot placement by measuring **step width**. In contrast to **COM signed deviation**, **step width** did not adapt with practice in the force field (Fig. 5). Thus, although previous research suggests that **step width** modulation is a primary strategy used to control COM motion (Kuo, 1999; MacKinnon and Winter, 1993; Maki and McIlroy, 1999), it is clear that in the current study participants were using other strategies to adapt COM trajectory. Alternative strategies utilized to adapt COM trajectory might have included changing ground reaction forces (Gruben and Boehm, 2012; Kim and Collins, 2015) or increasing muscle activations (Patla, 2003; Winter, 2009). Furthermore, we found immediate changes in **step width** when the field was either turned on or off. This absence of after-effects suggests that step width was likely a result of passive dynamics and/or feedback control of the swing limb (Rankin et al., 2014; Wang and Srinivasan, 2014), rather than an internal model. Our current experimental protocol is unable to differentiate these interpretations.

5. Conclusions

This study evaluated how people adapt motor plans of COM trajectory during goal-directed walking in a novel and consistent environment. We found that people form internal models to predict the COM trajectory that emerges from the interaction between a specific set of motor commands and the external environment. Our results may provide a framework for understanding how people plan and control walking.

Supplementary methods

To evaluate block order, statistical analyses were conducted using SPSS. We implemented one-way repeated measures ANOVAs with a between subject factor of block order to evaluate all metrics (**COM signed deviation**, **COM lateral offset**, and **step width**). We found no significant main effect of block order for all metrics; COM signed deviation (p = 0.136), COM lateral offset (p = 0.356), step width step one (p = 0.26), and step two (p = 0.219).

Data availability statement

https://doi.org/10.21985/N2WJ4M.

Declaration of competing interest

The authors declare no conflicts of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/0.1016/j.jbiomech.2019.07.030.

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