

Push-Recovery Stability of Biped Locomotion

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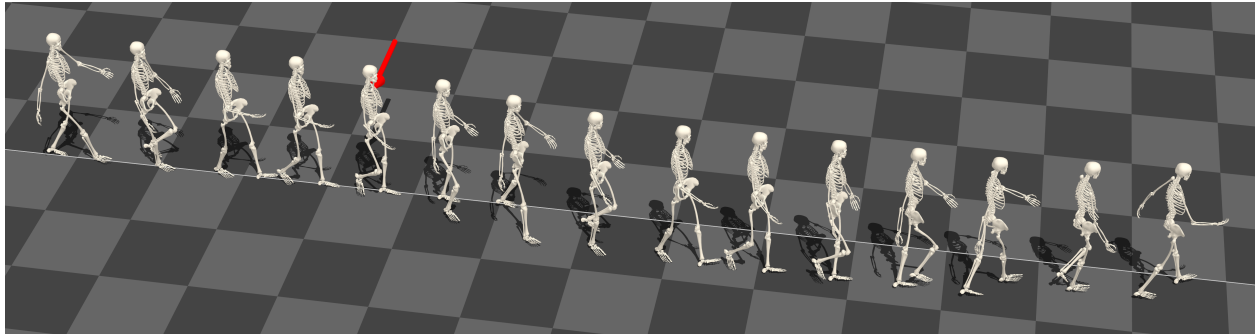


Figure 1: Motion capture of our push-recovery experiment. The experimenter pushed the participant while walking and measured lateral detour from the straight line.

Abstract

Biped controller design pursues two fundamental goals; simulated walking should look human-like and robust against perturbation while maintaining its balance. Normal gait is a pattern of walking that humans normally adopt in undisturbed situations. It has previously been postulated that normal gait is more energy efficient than abnormal or impaired gaits. However, it is not clear whether normal gait is also superior to abnormal gait patterns with respect to other factors, such as stability. Understanding the correlation between gait and stability is an important aspect of biped controller design. We studied this issue in two sets of experiments with human participants and a simulated biped. The experiments evaluated the degree of resilience to external pushes for various gait patterns. We identified four gait factors that affect the balance-recovery capabilities of both human and simulated walking. We found that crouch gait is significantly more stable than normal gait against lateral push. Walking speed and the timing/magnitude of disturbance also affect gait stability. Our work would provide a potential way to compare the performance of biped controllers by normalizing their output gaits and improve their performance by adjusting these decisive factors.

CR Categories: I.3.7 [Computer Graphics]: Three-Dimensional Graphics and Realism—Animation;

Keywords: Biped Locomotion, Control and Simulation, Gait Analysis, Balance, Stability

1 Introduction

Walking on two legs may appear to be unstable, as the body is statically unbalanced at any moment of locomotion. However, dynamic human locomotion is in fact inherently stable and resilient against modest perturbation. There exists a standard gait pattern that humans normally adopt when walking. The normality of gait has been defined based on appearance attributes, such as an upright body, straight knee in stance, sufficient foot clearance in swing, appropriate pre-position of the foot for contact, adequate step length, and a heel-ankle-forefoot rocker mechanism [Gage 2004]. Gait patterns that violate these traits are considered to be either abnormal or impaired.

Designing locomotion controllers is a central problem in physically based animation research. Biped controller design pursues two fundamental goals; simulated walking should look human-like (i.e., normal gait) and robust against perturbation while maintaining its balance. Although it has been postulated that normal gait is more energy efficient than abnormal or impaired gait [Collins et al. 2005; Waters and Mulroy 1999], many questions still remain regarding stability: Under what conditions is human gait more stable? What factors affect the level of stability? Is normal gait more stable than abnormal or impaired gait? Are biped controllers in physically based simulation as stable as human locomotion? Do the factors that affect human gait also influence the stability of biped controllers? These are the questions we seek to answer in this work.

These questions are closely related to designing biped controllers and evaluating their performance. Ideally, we wish to satisfy both goals simultaneously. However, it has been reported that state-of-the-art normal gait controllers are not the most robust under the presence of external perturbation [Wang et al. 2010]. We hypothesized that there exists a trade-off between energy-efficiency and robustness, meaning that gait and balance-recovering capability are highly correlated. Our goal is to identify which aspects of gaits actually affect balance-recovering capabilities. In previous work, the stability of biped controllers have often been demonstrated and compared by measuring the magnitude of external pushes the biped can withstand, regardless of gaits generated by the controllers. Some controllers generate gait patterns that match the description of normal gait, while the others generate peculiar styles, such as crouching and stomping. Given different output gaits, comparing

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their stability side-by-side might be unfair. Our work would provide a potential way to compare the performance of biped controllers unbiasedly by normalizing their output gaits and improve their performance by modulating decisive factors.

To test our hypothesis, we first conducted a set of experiments with thirty healthy participants, whose motions were captured using an optical motion capture system. Participants walked along a straight line using various gaits with different walking speed, stride length, and level of crouching. An experimenter applied a modest, impulsive force from the side by pushing the participant and measured the distance of the resulting lateral detour from the straight line. We conducted another set of experiments with a simulated biped, which walked in various simulated gaits and recovered its balance after external pushes. The simulated gaits were chosen from a multivariate normal distribution that matches the measurement data of human participants.

The statistical analysis identified four factors that affect locomotion stability. Moderate crouch gaits are significantly more resilient to external pushes than normal gaits, as generally believed. We also found that walking speed affected stability, as did the timing and magnitude of the disturbance. The same factors affected the push-recovery capabilities of both human and simulated walking. It turned out that the state-of-the-art biped controllers are not as capable as average humans yet, but their qualitative trends with respect to the four decisive factors are similar in our analysis.

2 Background

In computer graphics and robotics, there have been recurring efforts to design biped controllers that can simulate dynamic human walking, which has been implemented on both physical robots and computer simulation. It is well-known that a simple frame with two legs can walk down an incline in a human-like manner without any actuation and without control [McGeer 1990]. Inspired by such passive dynamic walking, Collins and his colleagues [2005] demonstrated a bipedal robot that walk energy efficiently. Animation researchers have been interested in the control of locomotion for humanoid characters. Many simulated controllers have been designed based on the principle of least effort, seeking optimal control policies that minimize either total joint torques, total muscle actuations, or metabolic energy expenditure [Wang et al. 2010; Wang et al. 2012; Geijtenbeek et al. 2013; Mordatch et al. 2013; Lee et al. 2014]. It is expected that the normal gait emerges in the process of minimizing effort. An alternative viewpoint is that normal gait is not represented by a unique gait pattern, but includes a wide range of gait variations. Data-driven controllers take an arbitrary (not limited to normal) gait pattern as input and track the pattern to simulate variations in human locomotion [Sok et al. 2007; Kwon and Hodgins 2010; Ye and Liu 2010; Lee et al. 2010].

The balancing mechanism for human locomotion is a complex process of the sensory-motor system. Several different approaches have been studied for modeling the balance mechanism. The first approach is based on explicit feedback rules, which are derived from simplified dynamics models such as SIMBICON [Yin et al. 2007] and inverted pendulum [Tsai et al. 2010; Coros et al. 2010]. Those feedback controllers tend to produce stereotypical stomping gaits that rise the swing knees higher than normal and lack heel-ankle-toe rocker motions of the stance feet. Such stomping gaits are avoidable as demonstrated in the subsequent studies. Lee et al [2010] employed SIMBICON-style feedback rules and motion capture data as a reference trajectory to produce a variety of human-like simulated locomotion. Wang et al [2010] began with SIMBICON as a base controller and applied stochastic optimization to tune the controller parameters so that the simulated gaits

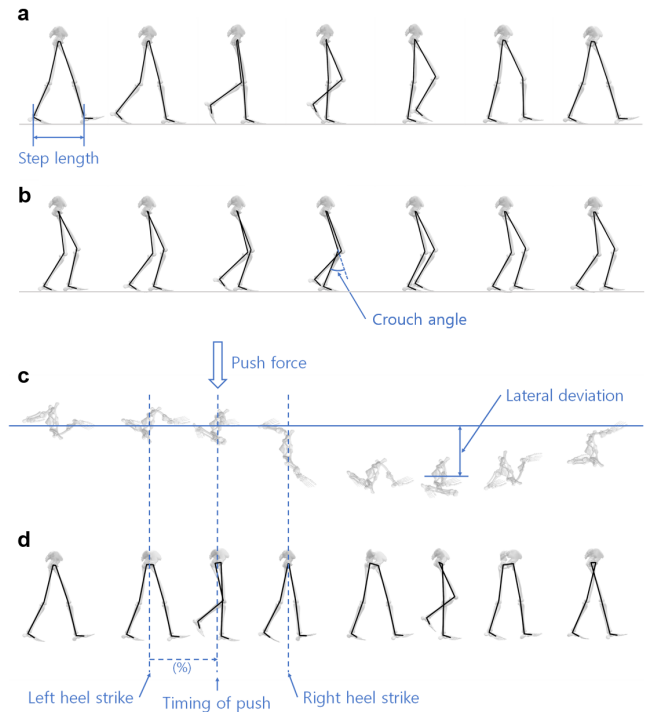


Figure 2: Biped human locomotion from motion capture. (a) The normal gait features the straight knee at mid stance, the dorsiflexed ankle at heel strike, heel-ankle-forefoot rocker mechanisms, and ankle push-off. (b) The crouch gait shows knee flexion at mid stance. The sole of the stance foot remains almost parallel to the ground throughout the stance phase. (c) Top view. We used a boxing pad to push the shoulders. The participants recovered their balance mostly within three steps and then returned to the straight line. (d) Side view. The timing of push is measured with respect to the left heel strike (0%) and the right heel strike (100%).

look more human-like. Notably, they reported that optimizing gaits in the presence of destabilizing conditions make the resulting gaits crouch.

Optimization techniques have been used in implementing balance strategies in various ways. Model-based controllers assume a base model of control policy and employ a nonlinear optimization technique to determine model parameters [Ye and Liu 2010; Wang et al. 2010; Wang et al. 2012; Liu et al. 2012]. Trajectory optimization directly manipulates either joint angles or torques over time to satisfy desired objectives and features [Mordatch et al. 2013; Al Borno et al. 2013]. Trajectory optimization usually produces a single gait pattern as the result of optimization. Regression over multiple perturbed gaits makes a responsive controller that can react to unexpected perturbation [Sok et al. 2007].

The stability of locomotion controllers have been demonstrated by measuring the resilience against external pushes [Sok et al. 2007; Yin et al. 2007; Lee et al. 2010; Wang et al. 2010], the change of body shapes [Lee et al. 2010; Coros et al. 2010; de Lasa et al. 2010], muscle weakness [Wang et al. 2012; Lee et al. 2014], and the change of environments (e.g., inclines, steps, and bumps on the ground surface) [da Silva et al. 2008; Lee et al. 2010; Coros et al. 2010]. Interestingly, stomping gait controllers [Yin et al. 2007; Tsai et al. 2010; Coros et al. 2010] reported better performance in push-recovery experiments (resilience against external pushes of 60 N·s to 194 N·s) than other normal gait controllers (resilience against

external pushes of 32 $N \cdot s$ to 92 $N \cdot s$). Jain and Liu reported that the stability of SIMBICON controllers can be improved with soft deformable bodies for the character's feet [Jain and Liu 2011]. Shitatori et al [2009] identified recovery strategies in human responses to tripping and created controllers for the trip recovery responses that occur during walking.

There have been continuing efforts to measure gait and postural stability quantitatively in biomechanics and neuroscience. Devices such as a motor-driven waist-pull system [Rogers et al. 2001] or a movable platform [Brauer et al. 2001] have been employed to generate quantified perturbations to study balance-recovering behavior from standing postures. Studies have measured the magnitude of kinematic variation or its temporal change as an estimate of gait stability in the presence of subtle or no disturbances. It has been reported that walking speed and stride length influence gait stability from the analysis of locomotion data of human subjects [England and Granata 2007; Bruijn et al. 2009] and a simple dynamic model [Bauby and Kuo 2000]. Those results do not apply to our experiments directly because we assume stronger, impulsive disturbances.

Hip extension during the stance phase and ankle push-off are two major power sources of normal gait to propel the body forward [Kuo 2002]. Normal gait is more energy efficient if the knees are straight during stance, as the muscles do not need to support the full body weight. Crouch gait is typically characterized by flexed knees in stance, weak ankle push-off, and the lack of heel-ankle-toe rocker motions [Rodda et al. 2004; Steele et al. 2010] (Fig. 2a, b), thereby relying heavily on hip extension and requiring more energy to bear the body weight during the stance phase [Waters and Mulroy 1999]. The stomping gait does not have flexed knees in stance, but shares the other characteristics (i.e., lacking ankle push-off and heel-ankle-toe rocker motions) of the crouch gait.

On the other hand, many humanoid controllers are derived from a simplified dynamics model with a point mass at the body and two fixed or retractable legs with no mass [Hirai et al. 1998; Goswami 1999]. Mapping the simplified model into articulated limbs may cause a mechanical singularity with straight legs, which limits the maneuverability of the foot along the vertical direction. Therefore, in order to prevent the knees from buckling, a crouch gait inadvertently results. Biped controllers based on computer simulation also suffer from similar problems [Tsai et al. 2010].

While previous locomotion control studies conducted push-recovery tests to demonstrate the robustness of their controllers, our goal is understanding principal characteristics of human locomotion and its stability. We hope to better understand how well existing biped controllers emulate human walking and how to improve controller design from the experiments.

3 Experiments with Human Participants

This study was approved by the institutional review board. A physician was present during all experiments, and received informed consent from all participants.

We conducted a series of experiments with thirty healthy participants (15 males/15 females). Their height varies from 154.6 cm to 181.2 cm and their weight varies from 41.9 Kg to 94.5 Kg. Participants walked along a straight line with various gaits. An experimenter pushed the shoulder of the participant using a boxing pad to apply a modest, impulsive force (Fig. 2c, d). The participants wore tight suits with retro-reflective markers for optical motion capture (Fig. 3a). The system used sixteen cameras (120 frames-per-second capture rate) to capture locomotion, pushing, and reaction. Vi-con's NexusTM software was used to reconstruct three-dimensional

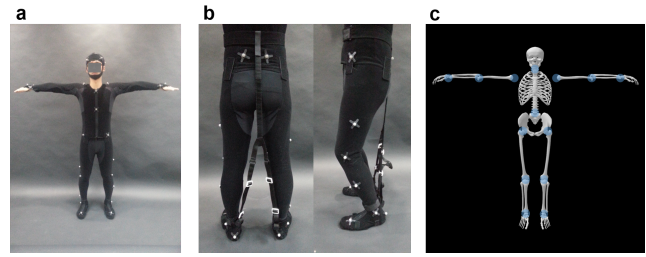


Figure 3: A participant in motion capture suit and our simulation model. (a) 43 retroreflective markers capture three-dimensional skeletal motion. (b) Adjustable straps make the participant crouch. (c) Our simulation model is a skeleton of rigid links connected by 14 joints. Each joint allows rotation of three degrees of freedom. The model weighs 48 kg and its height is 160 cm.

marker positions and skeletal motion, and to estimate the Center of Mass (COM) of the skeleton. We labeled the skeletal animation to annotate the moments of heel-strikes, toe-offs, push-starts, and push-endings in a semi-automatic manner. The magnitude of pushing was estimated from the change of lateral velocity of the COM over the duration Δt of pushing.

$$f = m(v^+ - v^-)/\Delta t, \quad (1)$$

where m is the weight of each participant, and v^- and v^+ are COM velocities in the lateral direction before and after pushing, respectively. In our experiments, the estimates of push forces vary in a range from 80 N to 200 N. Both total force $f \cdot \Delta t$ and normalized total force $f \cdot \Delta t / m$ were used for our statistical analysis.

To determine their reference walking speed and stride length, participants were first asked to walk with the normal gait that felt most comfortable. Then, they were asked to walk with the choice of two speeds (normal/slow), two stride lengths (normal/short) in random order. The push force was applied usually from left, as the participants were in single stance with only the left foot on the ground. The experimenter included variations in push direction (from left/from right), push timing (single stance/double stance and % in gait cycle, Fig. 2d), and push/no-push trial in random order. Each trial was repeated twice under the same condition. For the crouching condition, they walked at a self-selected speed and stride length in varying degrees of crouch ($0^\circ/20^\circ/30^\circ/60^\circ$). Straps were fitted to enforce crouch walking (Fig. 3b). The participants were asked to return to the straight line after pushing. The measurement data for each trial have 31 variables including angle of crouched knees, stride length, walking speed, the timing, magnitude and direction of the push (see Appendix for details).

In previous studies of biped control, the maximum disturbance a simulated biped can withstand has often been used as a stability measure. We could not adopt such a measure for our experiments with human participants because they might fall over while measuring the maximum push they can withstand. Instead, we used moderate, impulsive pushes they can cope with by taking a few detouring steps. The maximum lateral displacement of the participant's COM during three post-perturbation steps was found to be the most reliable measure of how stable the participant was during the disruption (Fig. 2c, d). It captures the effect of the initial sidestep, but also how quickly the participant recovers.

4 Simulation Experiments

We wish to determine whether computer simulation using a physically-based biped controller would respond similarly to exter-

nal pushes. We adopt a data-driven controller by Lee et al [2010] for our experiments since it easily generates gait variations by editing a reference gait pattern kinematically. This controller is equipped with full-body tracking capability for imitating reference gaits and feedback rules for maintaining its balance against external pushes. The source code for the controller is publicly available on the authors' webpage.

Parameter Optimization. Let τ be a full-body biped controller. Simulating the controller τ with a reference gait M generates simulated walking \hat{M} .

$$\tau(\theta; M) \rightarrow \hat{M}, \quad (2)$$

where motion M is a function of full-body poses varying over time $0 \leq t \leq T$ and may include multiple cycles of walking with a particular gait. An ideal tracking controller would reproduce the reference gait exactly in simulation, so $M = \hat{M}$. In practice, feedback controllers cannot reproduce the reference gait precisely, because of the discrepancy between human and simulated subjects, measurement errors in motion capture, and simulation errors in forward dynamics simulation.

The controller has adjustable feedback parameters θ that drive the tracking control to compensate for the deviation between simulated and reference gait patterns. The tuning of θ is moderately influenced by the choice of a reference gait. In the original work by Lee et al [2010], the parameters were tuned manually for each individual reference motion. In our experiments, parameter optimization determines feedback parameters automatically, and a single set of feedback parameters thus obtained are used for all gait variations. The optimization process runs the controller repeatedly and evaluates the performance under external perturbation using an objective function. Two test patterns were used for the evaluation: Normal gait and 60° crouch gait. The 60° crouch gait was chosen as the pattern that was most different from the normal gait. Even though only two test gaits were used for parameter optimization, the controller with optimized parameters can deal with a wide variety of gait patterns reliably in our experiments.

At each iteration of the optimization procedure, the controller runs the simulation of each test pattern for 10 seconds and an external push of 250 N is applied for 0.2 seconds at the middle of the simulation. The objective function

$$\arg \min_{\theta} E(\theta; M, \hat{M}) = w_1 E_{\text{balance}} + w_2 E_{\text{track}} + w_3 \|\theta\| \quad (3)$$

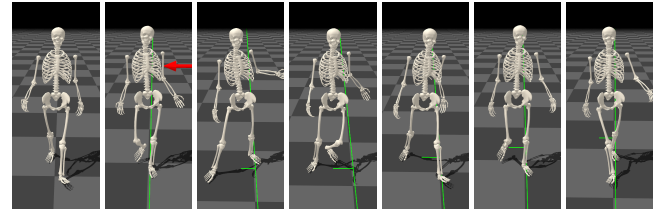
penalizes simulation results that entail either falling over or deviating from the reference gait pattern. More specifically, the balance term

$$E_{\text{balance}} = \begin{cases} 0, & \text{if it maintains its balance,} \\ T - T_f, & \text{if it falls over at time } T_f < T. \end{cases}$$

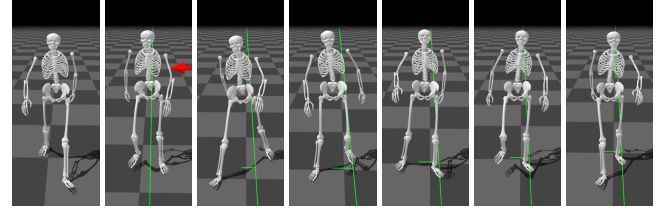
penalizes tripping in the middle of the simulation. The tracking term

$$E_{\text{track}} = \sum_{0 \leq t \leq T} \text{dist}(M(t), \hat{M}(t))$$

favors better tracking of the reference gait, where $\text{dist}(\cdot, \cdot)$ is a difference between two full-body poses [Lee 2008]. The third term regularizes the process to avoid excessive drifting of parameter values. The objective function is evaluated and averaged over two test gaits. In our experiments, the weight values are $w_1 = 1000$, $w_2 = 1.0$, and $w_3 = 0.1$. A Covariance Matrix Adaptation (CMA) [Hansen 2006] strategy is employed to search for optimal parameter values θ given the highly-nonlinear objective function. This process takes approximately 2.5 hours using 12 Intel Xeon X5670 2.93GHz CPUs with population size 50 and maximum iteration 600.



(a) A sample of the motion capture data.



(b) A sample of the simulation data.

	Human Participants Case No. 372	Simulation Case No. 2595
Level of Crouch	0°	0°
Stride Length	120cm	134cm
Walking Speed	121cm/s	121cm/s
Magnitude of Push	0.59N·s/kg	0.45N·s/kg
Timing of Push	44%	46%
Lateral Deviation	26cm	24cm

(c) Measurement data for the samples.

Figure 4: Samples chosen from the human and simulation data that look similar to each other. Both the human participant and the simulated biped regain their balance within the first post-perturbation step.

Push-Recovery for Gait Variations. The next step is to conduct push-recovery experiments with a simulated biped. To do so, a variety of gait patterns are required. Each gait pattern is fed into the optimized controller to drive the simulated biped, which will be pushed while walking as we did for human participants. We randomly selected one motion capture clip as a reference for normal gait and modified it to generate gait variations $M(\alpha_c, \alpha_1, \alpha_s, \alpha_f, \alpha_t)$ with five parameters, where α_c , α_1 , α_s , α_f , and α_t are random variables for the level of crouch, stride length, walking speed, the magnitude and timing of push, respectively. α_c is a categorical random variable that chooses a value uniformly from $\{0, 20, 30, 60\}$. The others are continuous random variables with normal distributions that match the measurement data from human participants. Gait variations are sampled from a multivariate normal distribution. The five parameters were chosen because they were turned out to be significant in the human experiment as will be discussed in the next section.

Each gait sample is instantiated from the reference normal gait by using hierarchical motion displacement mapping and timewarping [Lee and Shin 1999]. Hierarchical displacement mapping allows us to change the stride length of the reference gait and its level of crouching, while timewarping adjusts its walking speed. A gait pattern thus varied is included in the dataset if the biped walks with the particular gait and maintains its balance after random pushing at least for 10 seconds.

5 Statistical Analysis

We found that the lateral displacement peaks mostly within first three steps after perturbation. It means that the participant regained balance within three steps, and stopped deviating further, and returned to the reference line. In a few outlier cases, the participant failed to walk continuously after regaining balance or failed to return to the reference line, though no one fell over during the experiments. Such outliers are omitted from the analysis. We collected two groups of data. *Group 1* includes 228 cases of human data and 3,858 cases of simulation data, in which the lateral displacement peaked within one step (Fig. 4). *Group 2* includes 450 cases of human data and 13,707 cases of simulation data, in which the lateral displacement peaked within three steps. Having to take three steps to stop deviating further means that they experienced difficulties recovering balance. Both groups have cases only pushed from left. Note that *Group 2* is a super set of *Group 1*.

As noted, the simulation experiment collected substantially larger datasets than the human experiment did. We have liberty to run arbitrarily many trials with simulated bipeds. More data increase our confidence in statistical analysis. We draw more than enough samples for the 95% confidence interval because the simulation experiment is intended to cover the human experiment comprehensively with normal distributions that match the human experiment measurements.

Our experimental data have the stereotypical characteristics of measurement data in many medical and biological studies: Multivariate, repeated, unbalanced, and clustered. The data are multivariate and high-dimensional because the outcome (gait) is a time series of complex articulated structures. From each outcome, we collected measurements for 31 variables that might potentially influence the stability of gaits (see Appendix for details). Each participant is measured repeatedly (twice to be precise) on the same outcome. The data are unbalanced and clustered. It is difficult, if not impossible, to collect well-balanced data with so many variables in the experiment with human subjects. For example, our data include a lot more measurements from normal gaits than crouch gaits, and a lot more from normal-speed gaits than slow gaits.

The linear mixed model (LMM) is a general method for handling the between- and within-subject variability in the repeated, unbalanced data [Cnaan et al. 1997]. The term “mixed” comes from combining two types (fixed and random) of effects into a single linear regression model. Fixed and random effects are, in other words, population-average and subject-specific effects. We use a LMM to model the mean of detouring distances and assess covariate effects. The level of crouch is a categorical variable. The distance values for each crouch level were adjusted using a LMM with fixed effects and each participant as a random effect. The covariance structure is assumed to be variance components. Restricted maximum likelihood estimation is used to produce unbiased estimators.

Among many potentially influential variables, we need to identify a small number of fixed effects that significantly affect detour distance. To do so, we repeatedly chose a combination of three to five variables to build a LMM and evaluated its competence for the human dataset. The Akaike’s information criterion (AIC) and the Bayesian information criterion (BIC) are common tools for selecting among different competing models to fit a given data set. We found that a LMM with walking speed, push magnitude and timing as fixed effects minimized AIC and BIC (Table 1). The statistical analysis was conducted with the R (version 2.15.2). All statistics were two-tailed and p values < 0.05 were considered significant. The Bonferroni method is used for multiple comparison analysis.

	Level of Crouch	Linear Mixed Models
Human Participants ⁽¹⁾	Normal	$\alpha_d = 236.86 + 0.1898\alpha_f - 0.02969\alpha_s - 0.9951\alpha_t + 69.2396$
	20°	$\alpha_d = 236.86 + 0.1898\alpha_f - 0.02969\alpha_s - 0.9951\alpha_t + 13.1796$
	30°	$\alpha_d = 236.86 + 0.1898\alpha_f - 0.02969\alpha_s - 0.9951\alpha_t - 5.8181$
	60°	$\alpha_d = 236.86 + 0.1898\alpha_f - 0.02969\alpha_s - 0.9951\alpha_t$
Simulation ⁽¹⁾	Normal	$\alpha_d = 247.5 + 0.4645\alpha_f - 0.06404\alpha_s - 1.8498\alpha_t + 58.8934$
	20°	$\alpha_d = 247.5 + 0.4645\alpha_f - 0.06404\alpha_s - 1.8498\alpha_t + 36.7256$
	30°	$\alpha_d = 247.5 + 0.4645\alpha_f - 0.06404\alpha_s - 1.8498\alpha_t + 27.0606$
	60°	$\alpha_d = 247.5 + 0.4645\alpha_f - 0.06404\alpha_s - 1.8498\alpha_t$
Human Participants ⁽²⁾	Normal	$\alpha_d = 180.75 - 0.00562\alpha_f + 0.004871\alpha_s - 0.7063\alpha_t + 29.1812$
	20°	$\alpha_d = 180.75 - 0.00562\alpha_f + 0.004871\alpha_s - 0.7063\alpha_t - 26.6411$
	30°	$\alpha_d = 180.75 - 0.00562\alpha_f + 0.004871\alpha_s - 0.7063\alpha_t - 51.7153$
	60°	$\alpha_d = 180.75 - 0.00562\alpha_f + 0.004871\alpha_s - 0.7063\alpha_t$
Simulation ⁽²⁾	Normal	$\alpha_d = 424.51 + 0.6264\alpha_f - 0.1439\alpha_s - 1.3549\alpha_t - 64.5855$
	20°	$\alpha_d = 424.51 + 0.6264\alpha_f - 0.1439\alpha_s - 1.3549\alpha_t - 81.6353$
	30°	$\alpha_d = 424.51 + 0.6264\alpha_f - 0.1439\alpha_s - 1.3549\alpha_t - 62.1142$
	60°	$\alpha_d = 424.51 + 0.6264\alpha_f - 0.1439\alpha_s - 1.3549\alpha_t$

	Test for Fixed effects (F-value and p-value)							
	Level of Crouch		Magnitude of Push		Walking Speed		Timing of Push	
	F_c	p_c	F_f	p_f	F_s	p_s	F_t	p_t
Human Participants ⁽¹⁾	17.49	<.0001	13.42	0.0003	2.68	0.1098	14.35	<.0001
Simulation ⁽¹⁾	30.06	<.0001	17546	<.0001	106.56	<.0001	463.41	<.0001
Human Participants ⁽²⁾	8.35	<.0001	0.01	0.9297	0.03	0.8578	3.94	0.0479
Simulation ⁽²⁾	88.34	<.0001	19103	<.0001	371	<.0001	225.79	<.0001

Table 1: Linear mixed models that minimize Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The superscript (1) and (2) indicates Group 1 and Group 2, respectively. $\alpha_d, \alpha_s, \alpha_f, \alpha_t$ denotes detour distance, walking speed, push force and its timing, respectively. Grey cells are statistically significant ($p < 0.05$).

Group 1 Analysis. The Bonferroni test confirms that crouch gait is more resilient against external pushes than normal gait (Fig. 5 and Table 2). Normal gait was the most vulnerable to external pushes and the stability improves significantly with moderate (20° to 30°) crouching. Lowering the center of mass further down counteracts the benefits of crouching. The lateral detour distance is also related to walking speed and the magnitude of push force and its timing. It detours less if it walks faster, the push is weaker, and the push happens later in the swing phase. As predicted, gait stability is closely related to the ability to put the swing foot down quickly at an appropriate location. Improved maneuverability of flexed knees, high cadence, and late push timing allows the participant to plant the next stance foot quickly. Quantitatively, the significance of crouching ($F_c = 17.49, p_c < 0.0001$), push timing ($F_t = 14.35, p_t = 0.0001$), and push force ($F_f = 13.42, p_f = 0.0003$) for human participants are apparent. The analysis with simulation data confirms the significance of all four factors (p-values are smaller than 0.0001).

Group 2 Analysis. The Group 2 data include a lot of cases the participant panicked by pushes particularly with 60° crouch, so the trend of data is not as apparent as Group 1 analysis. Still, 20° crouch walk is significantly more stable than the normal gait ($t = 3.2, \text{adj } p = 0.0015$ for human data, and $t = 3.57, \text{adj } p = 0.0004$ for simulation data). Interestingly, the effect of push timing is evident ($F_t = 3.94, p_t = 0.0479$), while the effect of

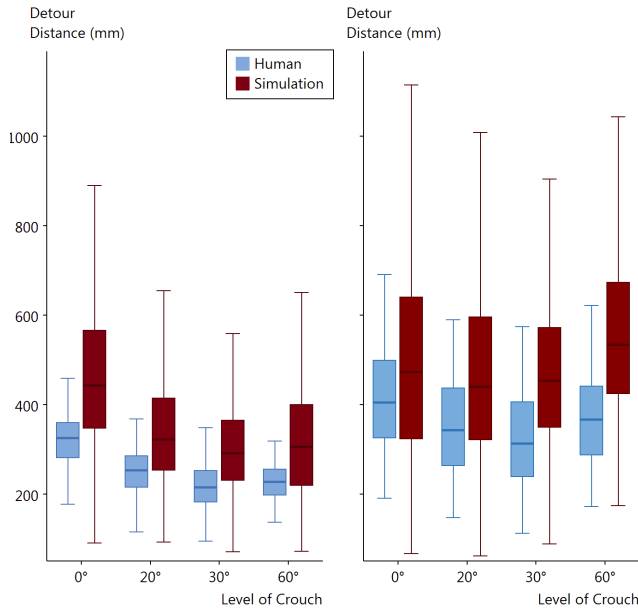


Figure 5: Box plots of detour distances by crouching for Group 1 (left) and Group 2 (right).

	Human Participants		Simulation	
	t-value	Adj p-value	t-value	Adj p-value
normal to crouch 20° ⁽¹⁾	4.47	<.0001	6.62	<.0001
normal to crouch 30° ⁽¹⁾	5.55	<.0001	8.3	<.0001
normal to crouch 60° ⁽¹⁾	5.09	<.0001	6.74	<.0001
normal to crouch 20° ⁽²⁾	3.2	0.0015	3.57	0.0004
normal to crouch 30° ⁽²⁾	4.57	<.0001	-0.48	0.6298
normal to crouch 60° ⁽²⁾	1.64	0.1013	-10.45	<.0001

Table 2: Bonferroni test for the difference of least squares means. Crouch gait at all levels detour significantly less than normal gait for both human experiments and computer simulation for Group 1.

push force is obscure with noisy human data. All four factors are significant with simulation data (p-values are smaller than 0.0001).

Categorical Analysis. We performed further analysis by using a linear mixed model with dependent variable Gait type (8) and categorical predictor Sex (M/F). The Gait type includes Normal, Slow, Short, Slow/Short, DoubleStance, Crouch20, Crouch30, and Crouch60 (Fig. 6). The post-hoc analysis using Bonferroni test for comparisons of means shows that the crouch gaits were indeed the most stable ($F = 65.12, p < 0.0001$), followed by normal gaits with a short stride, while the normal gait at slower speeds or when the push happened in the double stance were found to be least stable. There was an interaction effect with the sex of the participant ($F = 4.95, p = 0.0006$), where the benefits of crouch gait appear to occur mainly with the male participants.

Energy Expenditure. It is well-known that humans tend to select a preferred walking speed that minimizes their Cost of Transport (COT), which quantifies the amount of energy needed to move a body a unit of distance. The physiology literature reported a range of values from 1.05 meter/second to 1.4 meter/second, at which COT is minimized [Ralston 1958; Snaterse et al. 2011]. Simulated

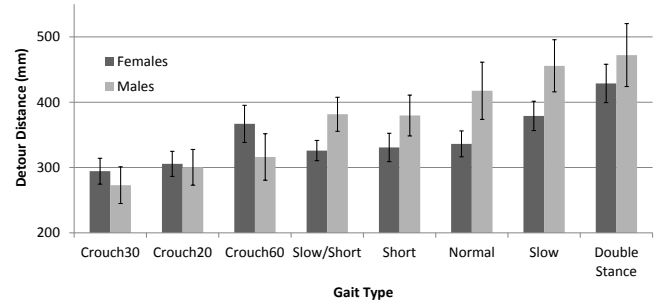


Figure 6: Mean detour distances by gait type.

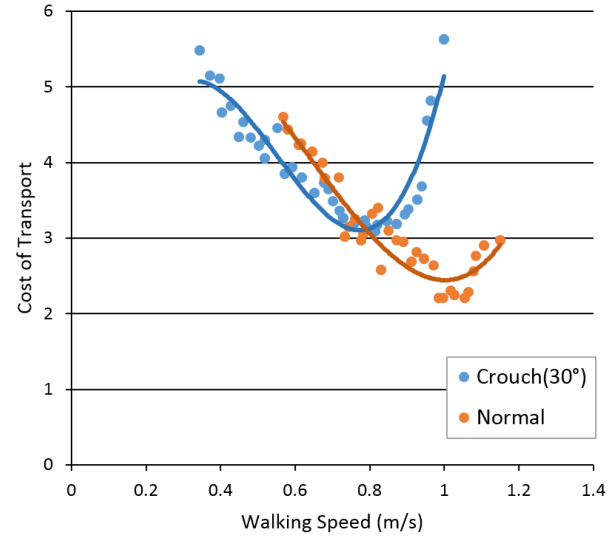


Figure 7: The relationship between cost of transport and speed of simulated walking. Cost of transport is dimensionless. To plot the relation, we generated a collection of simulated walking with a range of stride lengths and frequencies, and selected the most energy efficient stride/frequency combinations at a range of walking speeds. The cost of transport is computed using the mechanical work done by joint torques.

walking in our experiments are not as efficient as human walking. However, the COT plot of simulated normal walking is also parabola-like with its minimum at 1.0 meter/second, which agrees with previous studies on human walking (Fig. 7). As expected, normal gait is more energy efficient than crouch gait in simulation, and the COT of crouch walking is minimized at a slower speed.

Analysis with Stride Length and Stride Frequency. Walking speed is determined by both stride length and frequency. We conducted an additional analysis on the human dataset to understand how stride length and frequency influence gait stability. The LMMs in Table 3 show that shorter stride length and higher frequency tend to result in better stability (shorter detour distance). This observation is opposite to the results of previous studies, which reported that gait stability improves with longer stride length [Bauby and Kuo 2000; Bruijn et al. 2009]. Another previous study reported that slower walking speed improves stability [England and Granata 2007], which is also opposite to our observation showing faster walking speed is more stable (Table 1). The discrepancy comes from the use of different stability estimates and experimental se-

	Level of Crouch	Linear Mixed Models
Human Participants ⁽¹⁾	Normal	$\alpha_d = 268.35 + 0.170\alpha_f + 0.091\alpha_l - 157.094\alpha_q - 1.045\alpha_t + 49.649$
	20°	$\alpha_d = 268.35 + 0.170\alpha_f + 0.091\alpha_l - 157.094\alpha_q - 1.045\alpha_t + 11.804$
	30°	$\alpha_d = 268.35 + 0.170\alpha_f + 0.091\alpha_l - 157.094\alpha_q - 1.045\alpha_t - 4.213$
	60°	$\alpha_d = 268.35 + 0.170\alpha_f + 0.091\alpha_l - 157.094\alpha_q - 1.045\alpha_t$
Human Participants ⁽²⁾	Normal	$\alpha_d = 424.85 - 0.0282\alpha_f + 0.095\alpha_l - 87.686\alpha_q - 0.698\alpha_t + 13.278$
	20°	$\alpha_d = 424.85 - 0.0282\alpha_f + 0.095\alpha_l - 87.686\alpha_q - 0.698\alpha_t - 31.311$
	30°	$\alpha_d = 424.85 - 0.0282\alpha_f + 0.095\alpha_l - 87.686\alpha_q - 0.698\alpha_t - 54.296$
	60°	$\alpha_d = 424.85 - 0.0282\alpha_f + 0.095\alpha_l - 87.686\alpha_q - 0.698\alpha_t$

	Test for Fixed effects (F-value and p-value)									
	Level of Crouch		Magnitude of Push		Stride Length		Stride Frequency		Timing of Push	
	F_c	p_c	F_f	p_f	F_l	p_l	F_q	p_q	F_t	p_t
Human Participants ⁽¹⁾	8.12	<.0001	11.86	0.0007	11.44	0.0009	26.88	<.0001	17.28	<.0001
Human Participants ⁽²⁾	5.52	0.001	0.2	0.6582	5.83	0.0162	3.99	0.0464	3.9	0.049

Table 3: Linear mixed models with stride length and frequency. The superscript (1) and (2) indicates Group 1 and Group 2, respectively. $\alpha_d, \alpha_l, \alpha_q, \alpha_f, \alpha_t$ denotes detour distance, stride length, stride frequency, push force and its timing, respectively. Grey cells are statistically significant ($p < 0.05$).

tups. The previous studies used Lyapunov exponents and Floquet multipliers as estimates of stability, which describe how a small perturbation on a system affects its trajectory afterward based on the analysis of orbital trajectory variations. For example, a small Lyapunov exponent indicates initially nearby gait trajectories would converge rather than diverge. It assumes that kinematic variation is somehow related with dynamic stability. Push-recovery stability in our work measures resilience against impulsive perturbation. Neither resilience or orbital variation matches the general definition of dynamic stability precisely. These estimates illuminate different aspects of gait stability. Push-recovery resilience is effective when we want to understand how people cope with large, impulsive disturbances.

6 Discussion

To summarize the results, our statistical analysis identified significant factors that affect the push-recovery response in biped locomotion: the level of crouch, walking speed, push force and push timing. While the effect of crouching and push force were expected, the influence of speed and push timing were discovered inadvertently in our experiments. Height, weight, BMI were irrelevant. The analysis with detour distance normalized by the individual's height and push force not normalized by the weight does not affect the analysis.

Participants were aware that they would be pushed while walking, which may have had an effect on our results, as it may have allowed them to respond more quickly to the expected perturbation. We designed the experiments to mix push and no-push cases in random order. So, the participants may anticipate, but did not know precisely if he/she will be pushed at each trial. We also examined the anticipatory learning effect in the statistical analysis, but could not find any from the data.

It has previously been postulated that the foot-in-place balancing is dominant for static or low-speed motion, while foot placement plays a more important role for normal walking. In our experiments, participants took at least one balance correction step in every trial, so foot placement always affected balancing to some extent. Though we have not tried to verify the effects of foot-in-place

vs foot placement strategies, it is rather clear in the mocap data that the foot placement strategy critically affects the maximal detour distance. The biped controller by Lee et al [2010] generate balance feedback on both stance and swing legs, which emulate human balancing strategies. The feedback on the stance leg maintains the upper body upright (foot-in-place strategy), while the feedback on the swing leg adapts foot placement to recover its balance (foot placement strategy). It means that both strategies are employed by human participants and computer simulation, though they are not equally effective. Among the two strategies, foot placement correction plays a dominant role in our experiments.

The results show similar trends for human participants and computer simulation, though human participants performed better to lateral pushes than simulated feedback responses in quantitative measures (Fig. 5). Probably, the compliance of human joints absorbed the impact of pushing effectively, while the simulated joints were unnecessarily rigid, which might cause different push-response behaviors between human participants and simulated bipeds. The simplified, rigid feet of a skeletal model also affected the stability of simulated walking adversely. The use of a more detailed foot model would improve the stability of the controller.

Furthermore, it is likely that the correlation between gait and stability holds under the influence of other types of perturbation, such as pushing from arbitrary directions and slippery/uneven terrain, though this would require further studies to verify. Our simulation experiments were based only on the skeletal structure and its dynamics. Adopting musculotendon actuators would give us chances to understand physiological aspects of human locomotion, for example, functions of individual muscles when recovering from pushes. Biped simulation with musculotendinous units has recently been developed [Wang et al. 2012; Mordatch et al. 2013; Geijtenbeek et al. 2013; Lee et al. 2014], which will be a useful tool for investigating such physiological factors in the study of biped locomotion.

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Appendix: Experimental Data

We examined 31 gait factors that might influence its stability as comprehensively as possible, which include:

- sex (M/F), weight (kg), height (cm), BMI(kg/m²), left leg length (cm), right leg length (cm),
- crouch (0°/20°/30°/60°),
- stride (short/normal), actual stride (mm),
- speed (slow/normal), actual speed (mm/s),
- number of steps to maximal detour,
- maximal detour distance (mm), detour of the first step (mm),
- push start / mid / end (% in half gait cycle),

- push duration (s),
- push timing (single stance/double stance),
- push direction (from left/right of a participant)
- push force normalized ($\frac{1}{1000}$ N·s/Kg),
- push force not normalized (N·s),
- push force normalized by height (N·s/cm),
- push force normalized by leg length (N·s/cm),
- first, second, third rocker (second in gait cycle, % in half gait cycle),
- angle of the swing foot (with respect to the ground surface) at heel-strike (degree),

Specifically, the fixed effects of the linear mixed models in Table 1 are crouch, maximal detour distance, actual speed, push force normalized, and push mid. The experimental data are available online at <http://mrl.snu.ac.kr/research/ProjectPushRecovery/>.

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