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Technical note

Intra-session reliability of local dynamic stability of walking

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Abstract

While local dynamic stability measures have been successfully used to characterize walking stability, they require long continuous walking data, which may be difficult to obtain from a clinical population. We investigated the amount of walking data necessary to obtain reliable measures of local dynamic stability. Twenty healthy adults walked on a motorized treadmill at their self-selected speed for three trials of 5 min each. Trunk motion was used to construct a 12-dimensional state space comprised of the linear and angular positions and velocities. Mean divergence of locally perturbed trajectories was calculated as a measure of local dynamic stability using the first 1–5 min of data from each trial. Exponential divergence rates were quantified. Divergence was also parameterized using a double-exponential function. Intra-class correlation coefficients ICC(2,1) were calculated for each divergence measure for each trial length. ICC(2, 1) values increased with trial length, and reached 0.5–0.9. Good reliability was obtained for short-term measures for trial lengths of 2 and 3 min, but 5 min was not adequate to estimate the long-term coefficients based on a single trial.

Keywords: Reliability; Gait stability; Local dynamic stability; Walking; Treadmill

1. Introduction

Local dynamic stability has been used to study the dynamic stability of walking. Slower walking speeds exhibited by those with diabetic neuropathy compared to healthy adults may be an effective strategy to improve stability [1,2]. Stability during gait varies with walking speed separately from variability [3]. Stability during standing and walking are not correlated [4]. This method can assess dynamic stability without having to induce slips or trips which may be dangerous in certain populations [5,6].

While these approaches show potential as a clinical measure, estimating local dynamic stability requires that data be obtained from long continuous walking trials [7]. However, this may not be useful for testing patients who cannot walk for a long period due to pathologies or injuries. In this study, to determine the amount of walking data necessary to obtain a reliable measure of local dynamic stability, the reliability of local divergence metrics as a function of trial length was calculated.

2. Methods

Twenty healthy volunteers ages 18–73 (mean age 40) participated in this study after giving informed consent approved by the University of Texas Institutional Review Board. This wide age range was selected to study a potentially wide range of stability. Subjects were screened using a health-history questionnaire, and those with recent leg injuries, neuromuscular pathologies, and medications that could affect gait were excluded.

The subjects walked on a level treadmill (56 cm × 172 cm belt size, Desmo S model, Woodway USA, Waukesha, WI) for three trials of 5 min each, resting at least 2 min between trials to prevent fatigue. Subjects walked at their preferred speed, which was determined using a protocol described in [3]. A 3 m × 2.4 m ($w \times h$) blue

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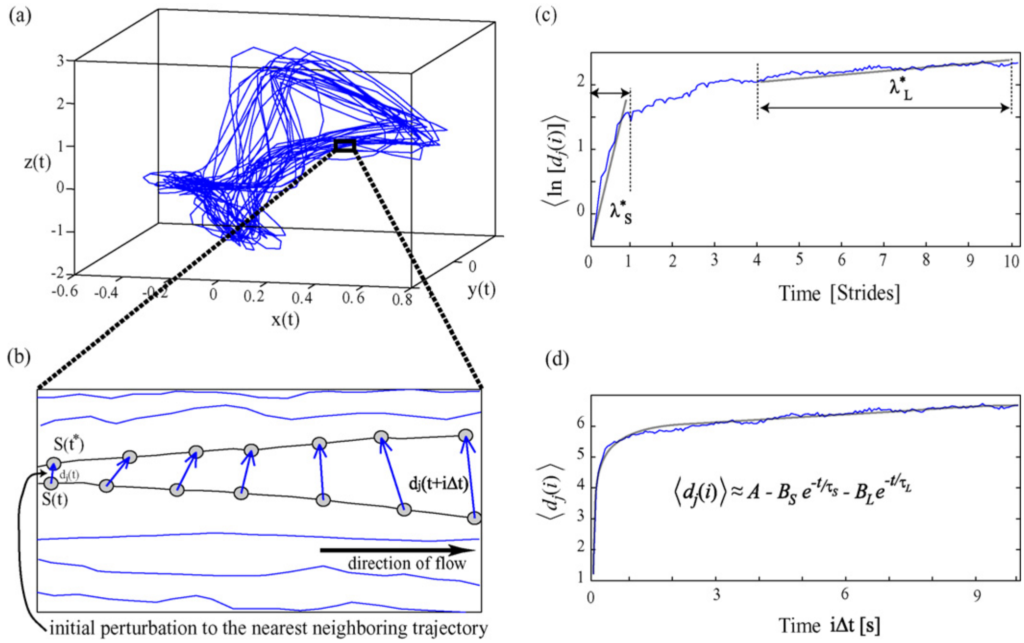

Fig. 1. Schematic representation of state space construction and local dynamic stability analysis for a single trial. (a) These states are combined to form the system's trajectory in state space (three states are shown for illustrative purposes). (b) Expanded view of a typical local region. A small perturbation moves the system at $S(t)$ to its closest neighbor $S(t^*)$. Local divergence is computed by measuring the Euclidean distances between the subsequent points, denoted $d_j(i)$. This is repeated over all points of the system trajectory in state space, and then averaged. (c) Exponential divergence rates were quantified by calculating the slope between 0 and 1 stride (λ^*_S) and between 4 and 10 strides (λ^*_L) of the mean log divergence curve. (d) A double-exponential function was used to parameterize the mean divergence curve.

screen was placed in front of the subjects to control visual input. Subjects wore a safety harness attached to an external support to prevent fall injuries. Trunk movements were sampled at 60 Hz using a VICON-612 system (Oxford Metrics, Oxford, UK). A rigid-body trunk model was defined by six markers placed on the left and right acromion processes and scapulae, and the 1st and 10th thoracic vertebral bony landmarks. We studied the motions of the trunk segment because over half of the body mass is located above the pelvis, which greatly affects the stability of the rest of the body [8]. A single researcher performed all marker placements and other experimental setups. Linear motions of the trunk were defined from the 3D excursions of the average location of all six markers, to minimize the effects of measurement noise and non-rigid behavior (bending, twisting, etc.). Rotational motions were defined using yaw–pitch–roll (*Z*–*y*–*x*) convention Cardan angles [4,9].

To account for the different units between linear and angular measures, both linear and angular displacements were demeaned and normalized to unit variance. Linear and angular velocities were then calculated from the normalized displacements using the three-point difference formula. These positions and velocities made up a 12-dimensional state space that fully described the dynamics of the trunk [4,9] (Eq. 1):

$$S(t) = [x, y, z, \quad \dot{x}, \dot{y}, \dot{z}, \quad \theta, \phi, \psi, \quad \dot{\theta}, \dot{\phi}, \dot{\psi}] \qquad (1)$$

where x, y, and z represent normalized linear displacements, $\dot{x}, \dot{y}$, and $\dot{z}$ represent linear velocities, θ, ϕ, ψ represent normalized angular displacements, and $\dot{\theta}, \dot{\phi}, \dot{\psi}$ represent angular velocities.

Subtle variations in the walking surface, visual or other sensory inputs, or neuromuscular noise provide small perturbations to the locomotor system [10]. Local dynamic stability of walking is defined as the quantitative response of the system's state variables (i.e., positions, angles, velocities) to these small perturbations [11]. When a system is perturbed while moving through its state space, the system will be "bumped" to a nearby part of the state space. The system's new trajectory may converge back or diverge away from the original trajectory. We estimate local dynamic stability by measuring, on average, how quickly the system will converge toward or diverge away from the original trajectory (Fig. 1).

For each point $S(t)$ at time t on the state space trajectory of the system, the nearest neighboring point $S(t^*)$ on an adjacent trajectory was determined, forming a pair of nearest neighbors [7]. For each pair j, the Euclidean distances $d_j(i)$ were calculated between each pair of points after each discrete time step i (i.e. $i\Delta t$ seconds, where Δt = 1/60 s) on the two trajectories (Fig. 2). This process was repeated for all points of the system trajectory with its nearest neighbor, and the $d_j(i)$ for each pair of points were averaged to produce the mean divergence as a function of time. The mean divergence behavior was parameterized in two ways.

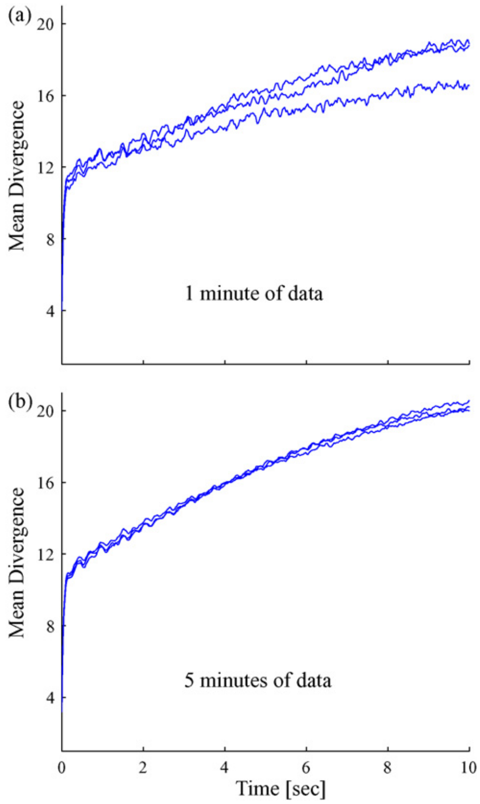

Fig. 2. Mean linear divergence curves from a typical subject. Each curve represents one trial (a) divergence curves calculated from 1 min of data and (b) divergence curves from 5 min of data. As trial length increases, the divergence curves show more consistency across trials.

The first method describes the divergence behavior in a log scale $\langle \ln d_j(i) \rangle$, time-normalized to the average stride time [1–3,12]. The slope of the mean log divergence curves were calculated as a measure of exponential rate of divergence (Fig. 1c). The slopes, λ_S^* and λ_L^* were calculated between 0 and 1 strides, and between 4 and 10 strides [1–3,12].

The second method quantifies the tendency of neighboring trajectories to converge or diverge in a linear scale (Fig. 1d) [4]. The mean linear divergence curves were parameterized using a double-exponential function Eq. (2):

$$\langle d_j(i) \rangle = A - B_S e^{-t/\tau_s} - B_L e^{-t/\tau_L} \quad (2)$$

where τ_S and τ_L ($\tau_L \gg \tau_S$) represent the time constants that describe how quickly $\langle d_j(i) \rangle$ approach the divergence limits. B_S and B_L determine how large of an effect each different timescale will have on $\langle d_j(i) \rangle$. This double-exponential fit Eq. (2) was used as an extension of the exponential divergence method described above, but does not require a subjective decision regarding where to compute these values [1,4,12].

To investigate the effects of trial length, mean log divergence slopes and mean divergence fit parameters were computed from the first 1–5 min of data from each of the three trials. This yielded three values of λ_S^* and λ_L^* as well as A, B_S, τ_S, B_L, and τ_L for each trial length per subject. The dependent measures were averaged across the three trials for each subject at each trial length, and a repeated-measures ANOVA was performed to test for any systematic differences in the parameters between the trial lengths. Dunnett's comparisons were performed to compare values at 5 min to shorter trial lengths.

To quantify intra-session reliability, intra-class correlation coefficients, ICC(2,1), were calculated for each dependent measure for each trial length using the three trials from 20 subjects Eq. (3):

$$\mathrm{ICC}(2,1) = \frac{\mathrm{BMS} - \mathrm{EMS}}{\mathrm{BMS} + (k-1)\mathrm{EMS} + \frac{k(\mathrm{RMS}-\mathrm{EMS})}{n}} \quad (3)$$

where BMS was the between-subjects mean square, EMS the error mean square, and RMS the between-raters mean square, k the number of raters (or trials), and n was the number of subjects tested, from a repeated-measure ANOVA [13]. ICC(2,1) is used in inter-rater reliability studies where the raters (or trials) are a representative sample from a population of raters [13]. Statistical analyses were performed using Minitab (Minitab, State College, PA).

3. Results

Both mean log divergence and mean divergence curves showed an initial steep rise and then a more gradual rise, similar to previous studies (Figs. 1c and d and 2) [1,3,4,12]. Age was not correlated with divergence parameters ($r^2 \leq 0.26$; $p > 0.05$). As trial duration increased, the fit parameters increased slightly, and between-subjects variance stabilized except for B_L (Fig. 3). Parameters from 3 and 4 min trials were not significantly different from 5 min trials, except for λ_S^* where values from 1–4 min trial durations were different from the 5 min trials, and for τ_s where no differences were found (Fig. 3).

For λ_S^* ICC(2,1) reached 0.75 by the third minute while increasing, while for λ_L^* it leveled off around 0.6 by the third minute. For the double-exponential measures, A and B_S both reached a plateau around the second minute, τ_S and B_L leveled off around the third minute, while τ_L steadily increased. Short-term measures λ_S^* B_S and τ_S reached ICC(2,1) of 0.8 and 0.9 by the second minute, but the other parameters did not (Fig. 4).

4. Discussion

It has been suggested that ICC values above 0.75 are indicative of good reliability [13]. This study demonstrated that good reliability can be obtained for the short-term

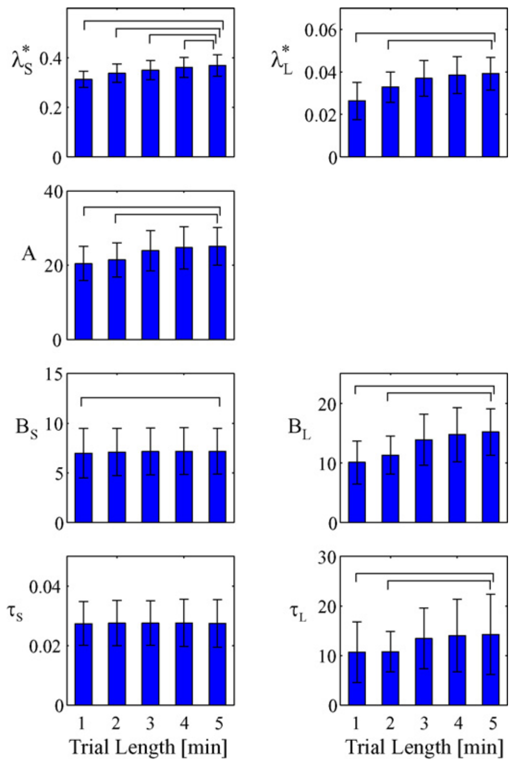

Fig. 3. Mean (±S.D.) of local dynamic stability measures as a function of trial length. Variability across subjects became consistent as trial length was increased. All measures seemed to approach a plateau as trial length increased. Significant differences (Dunnett's 95% confidence interval) in the parameters are shown with horizontal parenthesis.

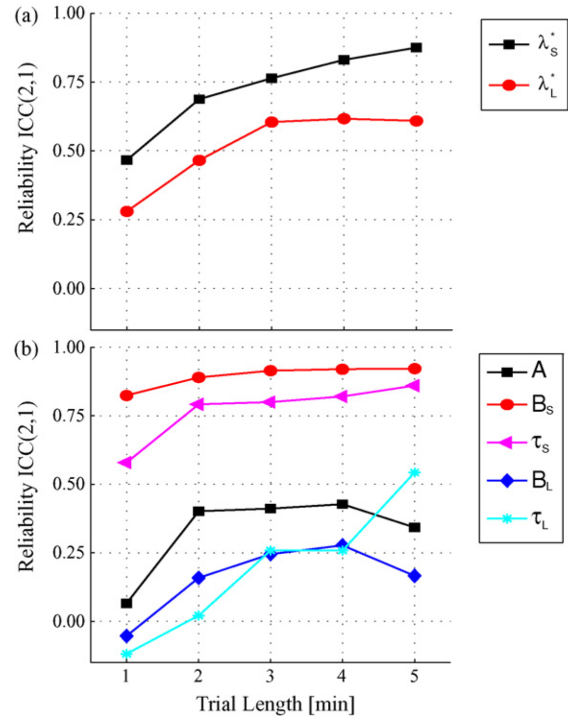

Fig. 4. ICC(2,1) values as a function of trial length. Across three walking trials, short-term measures showed good reliability with only 2 and 3 min of data, while long-term measures did not. (a) Short- and long-term slopes of the mean log divergence curves and (b) double-exponential fit parameters (Eq. (2)) of the mean divergence curves.

parameters with a trial of 2 and 3 min, but trial lengths up to 5 min were not sufficient to achieve good reliability for the long-term measures using just one single trial. Longer or multiple trials may be necessary to obtain reliable estimates of the long-term parameters. The ICC values in this were comparable to many other gait measures with ICC values of 0.67–0.95 [14,15].

The difference in reliability in the short- and long-term measures may be due to the fit criterion. The least-squares method used to fit the mean divergence penalizes r^2 more for deviations in the short-term parameters than long-term parameters. Or, the short-term measures may describe stability that is consistent within a person, while the long-term measures reflect the variability within a person among the three trials.

While this study provided preliminary values of reliability of local dynamic stability during walking, only one session of three trials was collected per subject, which does not allow the calculation of inter-session reliability. This study also included only healthy subjects, and not enough older subjects to see the effects of age on local dynamic stability. Future work will assess the local dynamic stability in other clinical populations who are at risk of falls such as older adults, and also establish within-session and inter-session reliability using longer walking trials and by averaging across multiple trials.

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