The Validation of Gait-Stability Metrics to Assess Construction Workers' Fall Risk

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ABSTRACT

Falling from height is the top cause of injuries and fatalities in the construction industry. Understanding the fall risk at different work environments can help to prevent fall accidents on a jobsite. While many previous studies attempted to assess the fall risk on a construction site, most of them are qualitative or subject to cognitive biases. In this context, this paper aims to introduce and validate a quantitative measure that allows researchers to characterize the fall risks of construction workers. In particular, this paper focuses on validating the fall risk predictive power of Maximum Lyapunov exponent (Max LE), which is one of the gait-stability metrics established in clinical settings. The kinematic data were collected using an inertial measurement unit (IMU) sensor attached to the right ankle of the subject performing different tasks. The Max LE for each tasks were then calculated based upon the IMU measurements. The results indicated a significant difference in the Max LE between different tasks, which indicates that Max LE has the potential to evaluate the dynamic stability of construction workers.

INTRODUCTION

In the construction workplace, slips, trips, and falls are the top cause of fatalities and injuries, a reality that affects productivity and equates to economic loss. Among construction trades, iron workers are at the highest risk of fall accidents (Teizer et al., 2013). While many previous studies attempted to prevent fall accidents through promoting design for safety, and the implementation of active and passive fall protection measures, the trend of fall accidents in construction industries have not yet been significantly decreased.

One of the most important steps toward preventing fall accidents is to understand the level of fall risks for each group of workers in different situations. The identification of a worker or a task with a high fall risk profile would lead to the effective implementation of fall prevention measures. However, current fall risk assessment techniques in construction mostly rely on experts' judgment, an approach that is subject to cognitive biases (Helander, 1991). Diverse measures to calculate the gait stability of a walking human and to indicate a person's fall risk have been introduced and utilized within clinical applications, including Maximum Floquet Multipliers (Bruijn et al., 2011), Maximum Lyapunov exponents (Chang et al., 2010), Stride Interval Dynamics (Jordan et al., 2007), and Detrended Fluctuation Analysis (Herman et al., 2005). Previous studies using these measures indicated that individuals do have different levels of fall risks. Some people tend to fall more often than others, even in the same environment (Liu et al., 2012).

While these metrics have proven useful in clinical settings, the feasibility of using these measures for characterizing fall risks in a dynamic construction environment has not been tested or demonstrated. One promising option for assessing fall risk is the Maximum Lyapunov exponent (Max LE), which is one of the most reliable gait stability measures. The Max LE measure quantifies local dynamic stability—which is the exponential attenuation of variability between neighboring kinematic trajectories—while assuming that each stride could be identical to other strides (England and Granata, 2007). The Max LE is able to detect the influences of external conditions on gait stability by using time series data captured via IMU sensors (Qu, 2013). The application of IMU sensors to assess the Max LE in construction settings could provide advantages over traditional laboratory instruments that measure balance and gait due to these sensors' mobility and price. In this context, this paper aims to use IMU sensors to validate the use of Max LE for assessing the fall risks of construction workers. In particular, this paper focuses on testing whether Max LE has adequate discriminating power to characterize the fall risks of iron workers.

RESEARCH OBJECTIVE AND METHODOLOGY

The objective of this paper is to examine the values of Max LE that appear while a subject performs different tasks that are hypothesized to have various levels of fall risks; subsequently, this paper seeks to validate the use of Max LE in characterizing the fall risk of construction workers. Also, this paper explores the possibility of utilizing IMU sensors for measuring the fall risks of construction workers. The procedures of the data collection and analysis are described in the following sections.

Participant. One experienced iron worker was involved in this study and was asked to perform different tasks (See Figure 1). The participant was reported to have no clinical conditions that could affect his gait. The participant reported that he is completely familiar with walking on an I-beam as an iron worker. (Age: 37 years; height: 5' 10''; weight; 210 lb; years of steel work experience: 15)

Instrument and Procedure. An IMU sensor (SHIMMER 9DoF, Shimmer) collected time series data of the participant's motion for each task. This IMU sensor was calibrated before starting the experiment so as to make it possible to compare the results of this test with the results of future tests conducted with the same sensor. The IMU sensor captured the accelerometer data (oriented with X-, Y-, Z-axes, representing anterio-posterior (AP), Vertical (VT) and medio-lateral (ML) directions of kinematic axes) and was attached to the right ankle of the participant. The time series data were connected via a Bluetooth connection with a sampling rate of 52 Hz. A video camera was placed near the I-beam to capture the motion of the participant for future analysis. The participant was asked to wear a work sleeve shirt, a safety harness, a pair of safe boots, and a hard hat in order to minimize the effect of clothing and shoes on data collection.

Figure 1. Illustration of the experiment: (a) I-beam used in the experiment; (b) walking at his comfort speed; (c) carrying a load on one side; (d) walking with a faster speed; (e) walking with a safety harness lanyard connected to the I-beam; (f) walking on the lower flange of the I-beam; (g) the IMU sensor attached to the right ankle of the ironworker.

The participant was instructed to perform 5 different walking tasks. In the first task, the participant walked along an installed I-beam at a comfortable speed (Task 1 in Table 2, See Figure 1-b). For the second task, the participant carried a toolbox bag weighing 25 pounds on his right side (Task 2 in Table 2, See Figure 1-c). Since carrying a load is known to be one of the contributing factors to decreased local dynamic stability (Qu, 2013), it was hypothesized that carrying physical loads would adversely affect local dynamic stability during gait and increase the fall risks of iron workers. In the third task, the participant walked with the fastest speed he could capably walk; after the test, the speed of the participant was calculated by using the captured video (Task 3 in Table 2, See Figure 1-d). It was hypothesized that increasing the iron worker's walking speed would increase the fall risk of the construction workers.

Lastly, the participant were asked to perform two common ways of walking on the I-beam on an actual job site. One of these ways is to walk while the lanyard of his safety harness is connected to the I-beam using a sliding I-beam anchor (Task 4 in Table 2, See Figure 1-e). The second way was to walk on the lower flange of the I-beam; in this task, the participant leaned down and contacted his two hands on I-beam to assist in balancing his body during movement. The walking style in this situation is very near to a crawling movement (short and fast strides). The participant was then able to make a faster speed than normal speed since he was able to maintain his body balance well in a high speed movement. (Task 5 in Table 2, See Figure 1-f).

For each task, the participant kept walking for at least two minutes since trial lengths of two minutes are found to be sufficient enough to ensure that the exponential divergence of kinematic trajectories in calculating Max LE are stabilized (Kang and Dingdwell, 2007).

Table 1. Summary of the tasks studied in this research

	Description	**Avg. walking speed (m/s)**	**No. of steps**
Task 1	walking at his comfort speed	5.22	18
Task 2	carrying load on one side	5.54	17
Task 3	walking with a faster speed	7.48	19
Task 4	walking with lanyard of safety harness connected to the I-beam	6.1	16
Task 5	walking on the lower flange of the I-beam	7	23

Local Dynamic Stability Calculation. To calculate Max LE, this paper uses the Rosenstein algorithm (Rosenstein et al., 1993), which determines the Euclidian distance between all probable combinations of data point in the time series data set.

The first step in calculating Max LE is to select a proper state space with enough dimension to appropriately capture the dynamics of the analysis system. Time series are a scalar sequence of measurements taken at a fixed sampling rate that can be used to reconstruct a state space with adequate dimension (Dingwell and Cusomano, 2000). A state space is a space defined by the unique dimensions required to examine the target dynamic motion. Embedding dimension and time delay are two parameters that are required for modeling the state space construction. Phase space can be shown as a multivariate vector in a d-dimensional space:

$$X(t) = \left(x(t), x(t+T), x(t+2T), \dots x(t+(d_E-1)T)\right) \quad (1)$$

Where x (t) coordinates in the phase space (Eckmann and Ruelle, 1985), T is time delay, and d_E is an embedding dimension.

Global false nearest neighbors (GFNN) method is used in this paper to select the perfect embedding dimension (Abarbanel and Kennel, 1993; Kennel, et al. 1992).

Auto mutual information approach (Cao, 1997) was used to calculate the proper time delay. Local dynamic stability can be assessed by tracking the average of the divergence from the nearest kinematic trajectory:

$$d_t = D_0 e^{\lambda_{MAX} t} \qquad (2)$$

where D_0 is the average distance between trajectories at t=0, d_t is the average Euclidean distance between initially neighboring trajectories at time t, and λ_{MAX} is calculated as the slop of the curve generated by this equation (England and Granata, 2007):

$$y(i) = \frac{1}{\Delta t} < \ln d_j(i) > \qquad (3)$$

In the above equation (3), Δt is the sampling frequency, $d_j(i)$ is the distance between the jth pair of nearest neighbors at the time i, and $< \cdots >$ denotes the average of the contents (Rosenstein et al., 1993).

The higher Max LE means that the divergence from one trajectory to another grows faster and then the local dynamic stability of human control system is lower (Liu et al., 2012). In this research, data for 2 minutes of walking for each task (6240 data samples) were recorded. The embedding dimension (d_E) and the time delay (T) were estimated for each direction of each task. The estimated embedding dimension, time delay, and the number of walking steps for each axis of each task are summarized in Table 2. Then the Max LE λ_{MAX} in finite time span (short-term Max LE) for each axis was calculated with the estimated embedding dimension and time delay as the slope of the equation 3 with regards to the data for the first 65 feet. A MATLAB program was used for all of the computation (ver 8.1.0.604, The MathWorks Inc., USA).

Table 2. Summary of gait parameter in different tasks

	Direction	Embedding dimension	Time delay
Task 1	AP	5	5
	VT	3	
	ML	3	
Task 2	AP	6	4
	VT	3	
	ML	3	
Task 3	AP	6	6
	VT	7	
	ML	4	
Task 4	AP	5	4
	VT	5	
	ML	5	
Task 5	AP	8	3
	VT	5	
	ML	4	

RESULTS AND ANALYSIS

Figure 2 shows the calculated Max LE values for each direction of each task. The highest Max LE was found in VT direction of Task 3 as 0.52, while the least value was found in ML direction of Tasks 4 as 0.13. Again, the higher Max LE value indicates the lower local dynamic stability of human control system, which can be interpreted as having a higher fall risk.

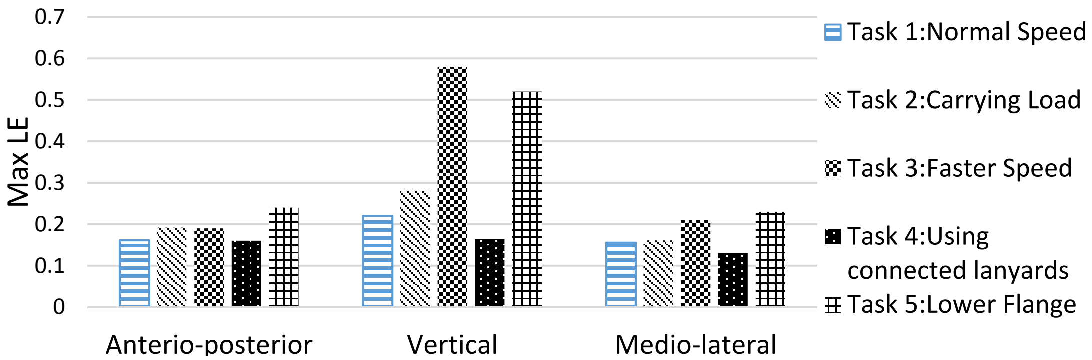

Figure 2. Max LE values for each task

The results show that there are clear differences between the Max LE of different tasks. The Max LE values of Task 2 are higher than Task 1 in all of three axes; this result is in accordance with our hypothesis that carrying a load has an adverse effect of the subject’s dynamic stability. Also, the Max LE values of Task 3, in which the subject walked with a faster speed, are higher than Task 1. This result is also in accordance with the assumed level of fall risks related to walking speed. These findings demonstrate that Max LE could capture the change of ironworkers’ fall risks due to carrying load and moving faster.

The Max LE values of Task 4 were lower in VT and ML directions compared to Task 1. This result can be explained in relation to the walking speed of Task 4. Dragging the lanyards of his safety harness, which was connected to I-beam via a sliding I-beam anchor, caused the subject to walk slower and use shorter strides as compared with Task 1. This change in speed may increase the local dynamic stability of the subject. On the other hand, The Max LE values of Task 5 are found to be much higher than Task 1 even though this style of movement is considered to be more stable since contacting hands on an I-beam helps an ironworker maintain his balance during his movement. This result may be due to the sensor location on the body. During Task 5, the stability of the subject’s upper body may has been well-maintained due to the use of his hands, but his legs showed more diverse lateral movement in each gait to avoid the contact with the web and top flange parts of the beam. Such an inter-variability of leg movement between steps may have impaired the Max LE measurement at the ankle of the subject. The Max LE measurement at the upper body of the subject during Task 5 may indicate the difference in results and could be one of the future directions of this research.

Also a significant difference was found in the Max LE measurements among the three different directions, though the comparison of Max LE measurements among different tasks shows quite similar trends across the different directions. In particular, the Max LE measurements in VT direction shows greater differences between tasks that have different fall profiles. This indicates that Max LE measurements in VT direction may provide a better discriminating power in characterizing iron workers' local dynamic stability.

CONCLUSION AND FUTURE RESEARCH

This paper aims to provide and introduce a gait stability measure that can quantify the fall risk of construction workers. The experiment results show that walking tasks with high fall risk profiles bring about higher values of Max LE compared with stable walking motion except when the task involves the use of other body parts for maintaining body balance. These results indicate the possibility of using Max LE as a quantitative measure to characterize the fall risks of construction workers and tasks. Also, this paper demonstrates the capability of using IMU sensors to capture kinematic data necessary for assessing the dynamic stability of a construction worker.

Future research will further validate the feasibility of using Max LE measurements in assessing iron workers' dynamic stability through additional experiments with a meaningful number of subjects and will also look at the differences of Max LE measurement between subjects.

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