Sensing Workers Gait Abnormality for Safety Hazard Identification

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Abstract –

Ironwork is considered one of the most dangerous construction trades due to its fall-prone working environment. Since safety-hazard identification is fundamental to preventing ironworkers' fall accidents, engineering measures have been applied to eliminate fall hazards or to reduce their associated risks. However, a significant quantity of hazards usually remains unidentified or not well assessed because most current efforts rely on human judgment to identify hazards. To enhance hazard identification efforts, this paper develops a technique for detecting the jobsite safety hazards of ironworkers by analyzing their gait anomalies. Using wearable inertial measurement units (WIMUs) to record kinematic data about ironworkers' gait, this study collected kinematic data while the workers interacted with two types of jobsite hazards. The anomaly level of each gait was modeled using diverse gait-related metrics. Moreover, relationships between safety hazards and worker gait abnormalities were examined through extensive experiment evaluations. The results reveal opportunities for enhancing hazard identification performance by monitoring workers' bodily response.

Keywords – Hazard Identification; Gait Analysis; Inertial Measurement Units; Safety management

1 Introduction

Hazard identification is the critical first step in the construction industry's safety-management programs [1] since unidentified hazards negate the whole safety-management process [2]. However, a significant quantity (on average 10 ~ 57%) of hazards in a construction project still go unidentified or not well-assessed, and these unidentified hazards present the most unmanageable risks [1,3,4]. Poor hazard-identification performance stems from the fact that most current efforts rely on human judgment to identify hazards [1,4,5], a reality that faces twofold challenges: 1) It is unlikely that an individual possesses all the knowledge and experience necessary to identify every potential hazard [1]. 2) Dynamic and unpredictable construction environments compound the complexity for individuals seeking to recognize hazards [1,4]. Furthermore, considering the fact that most hidden hazards are beyond the threshold of human recognition or are not defined with explicit knowledge, there is a critical need to enhance hazard recognition capabilities beyond the threshold of human recognition abilities.

In this context, our study examines whether recording data about workers bodily and behavioral response patterns can enhance hazard-identification capabilities in construction. Thanks to the fact that safety hazards generally cause disruptions in workers' behavior patterns, the analysis of workers behavioral and bodily response patterns provides valuable information that can be used to identify hazards. Toward this end, this paper investigates the feasibility of utilizing workers gait information—specifically, the spatiotemporal features of workers' gaits—to estimate the existence of fall hazards on the surface. In particular, this study develops wearable inertial measurement units (WIMU) -based Gait Abnormality Score (I-GAS) to effectively represent multiple gait features in a single score for detecting the existence of hazard. In turn, this study examines to what extent I-GAS's performance reveals hazards in a laboratory setting. For validation, this study designed and conducted laboratory experiments simulating ironworkers' working environment. Through these experiments, we collected participants' gait data using WIMUs. The results of the experiments demonstrate the potential of using collective gait information to detect fall hazards in construction.

2 Research Background

Most current hazard identification techniques in a construction project rely on individual workers' recognition skills. Previous studies on safety hazard identification have thus focused on enhancing individual workers' hazard-recognition abilities via training programs and virtual environments [1,5]. While these studies have advanced hazard responsiveness, they are still limited by workers' ability to recognize hazards and/or by workers' existing knowledge of known hazards. Furthermore, human recognition abilities are highly subject to diverse environmental factors, such as low light, noise, and jobsite organization. For instance, a slippery/contaminated surface—the destructive causal factor of fall accidents in several trades—is hard to identify in low-light conditions. Moreover, manual material handling (e.g., carrying, pulling and pushing) is generally required during the construction work process, and it often interferes with visibility in the workplace [6].

To mitigate this reality, several studies examined the potential of applying diverse sensing approaches [7–11] to construction safety. Computer vision-based techniques are used to detect workers' unsafe behaviors [7] and hardhat wearing [8] in a construction environment. However, the applications of vision based techniques have several challenges, including the limited sensing range of a camera and visual occlusions.

With the development of wearable sensing devices and technology, workers' physiological responses—such as heart rates, breathing rates, and postures—have been monitored and studied for enhancing safety and productivity in previous studies [9–12]. Our previous studies [13,14] also investigated the feasibility of detecting near-miss falls of ironworkers using sensed bodily response. However, previous studies focused on detecting workers' unsafe behaviors and/or their exposure to recognized jobsite hazards, rather than on identifying and assessing a hidden hazard discovered through sensed data.

It is well known that safety hazards can cause disruptions in workers' behavior patterns, which may then result in undesired events or accidents [15]. Therefore, analyzing the abnormality in workers' behavior patterns provides an opportunity to identify hidden hazards. In particular, by analyzing workers' gaits, researchers can gain valuable insights regarding fall hazards that may cause slips, trips, and falls.

Gait analysis in clinical applications has been widely used to assess the fall risks of health-care patients or elderly individuals who have gait disorders [16,17]. Gait is defined as a particular way of walking [18]. For gait analysis, a maker-based system and a floor sensor-based system have been widely used in previous studies [17,19]. However, these systems are only able to collect gait information in the laboratory setting. Given the need for an ambulatory gait-monitoring system, some studies used WIMU sensors in gait analysis for fall-accident prevention and evaluated these sensors' performance [17, 18]. Using the kinematic data captured via WIMUs, researchers computed spatiotemporal gait features (e.g., stride time and stride distance) to assess abrupt changes in patients' gait patterns and to measure the risk of falls [20,22,23]. While such gait analysis has been used for patients, there are no previous attempts to use it for identifying hazards in construction environments.

Computed gait features may capture the disruption in workers' gait patterns caused by safety hazards, but it is not certain whether each feature is sensitive to all types of hazards. Moreover, each gait feature has a different range of values with different measurement units. Thus, to comprehensively assess the gait abnormalities caused by hazards, it is necessary to represent the deviations of all the gait features from a normal gait in a single score. Expanding upon previous studies, this paper will compute the gait features of workers and use them to analyze the abnormality in workers' gait patterns.

3 Methodology

3.1 Gait Analysis and Gait Feature Computation

During a gait, the sensor coordinate system—the coordinate axes of the WIMU sensors attached to workers' ankles—are not aligned with the human body coordinate system—the coordinate system of the workers' body represented by the anterior-posterior, mediolateral, and vertical axes. This misalignment is due to the difference between the ankle-movement direction (cyclic between the floor, the height of the step, and the foot's forward motion) and the gait direction (i.e., walking forward). Thus, determining the angle between the body coordinate system and the sensor coordinate system (theta in Figure 1) is necessary to calculate the workers' gait features (such as stride length and velocity) using the data garnered from the WIMU attached on the ankle.

As illustrated in Figure 1 (left), the orientation angle between these coordinate systems continues to change by the location of the ankle during a gait. To calculate orientation angle of WIMU, this study utilized the rotation matrix to project the acceleration from the sensor coordinate system to the body coordinate system; this study used the quaternion ($\mathrm{q} = \mathrm{q}_r + \mathrm{q}_i\mathrm{i} + \mathrm{q}_j\mathrm{j} + \mathrm{q}_k\mathrm{k}$) format, which is available method to represent the rotation of an object using a complex number [24].

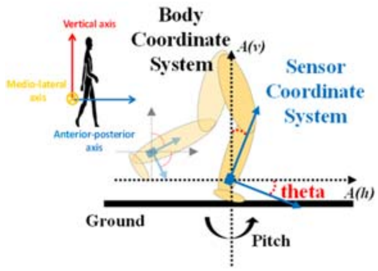

Figure 1. Sensor coordinate system and body coordinate system during gait

Projected acceleration for the gait analysis (i.e., for the body coordinate system) were then computed by multiplying the rotational matrix (Rm)—which we derived from the quaternion (See Equation 1)—and the collected acceleration values from the WIMU sensors.

$$\begin{bmatrix} 1-2{q_j}^2-2{q_k}^2 & 2(q_iq_j-q_kq_r) & 2(q_iq_k+q_jq_r) \\ 2(q_iq_j-q_kq_r) & 1-2{q_i}^2-2{q_k}^2 & 2(q_jq_k-q_iq_r) \\ 2(q_iq_k-q_jq_r) & 2(q_jq_k-q_iq_k) & 1-2{q_i}^2-2{q_j}^2 \end{bmatrix} \quad (1)$$

To compute the horizontal velocity (i.e., velocity of anterior-posterior axis, V_h) and vertical velocity (i.e., velocity of vertical axis, V_v), this study found the integral of the projected horizontal and vertical acceleration values (A_h and A_v in Figure 1). Since acceleration data from WIMU sensors already contain the effect of gravity ($9.81\ \mathrm{m/s^2}$), this effect was offset from the rotated acceleration value of the vertical axis.

The next step for computing the gait features is to detect gait events, such as toe off (TO) and heel strike (HS), to define the gait cycle. The gait cycle is defined as the time between two successive occurrences of one of these events during walking [25] (See Figure 2).

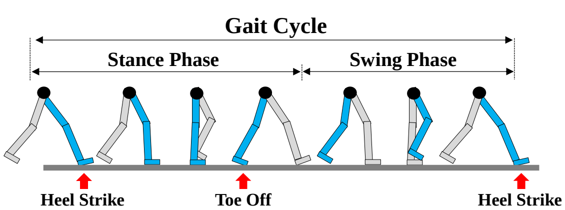

Figure 2. Definition of a gait cycle and gait events

In general, heel strike, the moment when a foot contacts the ground, is widely used to define a gait cycle, although any gait events can be used [26]. Thus, based on other gait analysis studies [15,16,19,20], this study defined a gait cycle as a gait between consecutive heel strikes of one foot. Since this study utilized heel strike as the starting point of the gait cycle, the initial gait cycle before the first heel strike point is neglected in our gait feature computation.

The gaits events (HS and TO) can be directly identified from the pitch angle of a gyroscope [28] inside the WIMU sensor (see Figure 3).

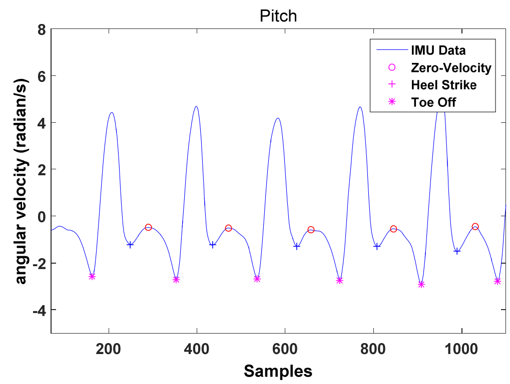

Figure 3. Heel strike, toe off and zero-velocity points with angular velocity in pitch

Based on the defined gait cycle, this study computed the four gait features—stride time, stride distance, average velocity and maximum foot clearance—for each gait cycle as follows:

- Stride Time, ST:
  Time between heel-strike points of one foot.
  $$ST = HS_{i+1} - HS_i \quad (2)$$
- Stride Distance, SD:
  Distance covered during a gait cycle.
  $$\mathrm{SD} = \int_{HS_i}^{HS_{i+1}} \mathrm{V}_h(t)\, dt \quad (3)$$
- Average Velocity, $\overline{\mathrm{V}_h}$:
  Average of horizontal velocity during a gait cycle.
  $$\overline{\mathrm{V}_h} = \frac{1}{HS_{i+1} - HS_i} \int_{HS_i}^{HS_{i+1}} \mathrm{V}_h(t)\, dt \quad (4)$$
- Foot Clearance, FC(t)
  Foot height from the ground during gait at time (t), finding an integral of vertical velocity (V_v) at time (t).
  $$\mathrm{FC(t)} = \int_o^t \mathrm{V}_v(t)\, dt \quad (5)$$
- Maximum Foot Clearance, FC_{max}:
  The maximum value of foot clearance during a gait cycle.
  $$\mathrm{FC}_{max} = \max_{t\,\in\,\{HS_i,\cdots,\,HS_{i+1}\}} FC(t) \quad (6)$$

where HS_i, HS_{i+1} are the time of i[th] and (i+1)[th] heel strike events.

Sensor drift is another issue in computing gait features from WIMU measurements [29]. This study used the zero-velocity assumption and zero-velocity update (ZUPT) to compensate for drift errors in gait-feature computations. Previous studies [22,28,30] have widely used the zero-velocity assumption to offset sensor measurement errors and drifts; this assumption says that the velocity of the foot is zero when the foot is located horizontally on the ground, which is why this location (the ground) is also known as the zero-velocity point. The zero-velocity update (ZUPT) method compensates for drift errors in velocity computations by updating a zero value for each zero-velocity points during a gait. This study used the pitch angle of the WIMU's gyroscope to identify the zero-velocity point same as gait event identification (see Figure 3).

3.2 Gait Abnormality Score Measurement

The clinical domain develops and uses the Gillette Gait Index (GGI) to measure the gait abnormality of patients in a single score [16]. GGI utilizes 16 gait-related features (e.g., mean pelvic rotation, total range of knee flexion–extension and mean foot progression angle) computed from an optical device with markers (e.g., VICON). Then, it performs principal component analysis, which is a widely used method to remove correlation between features, and measures the distance (i.e., Euclidean) of gait feature values between a specific test subject and a healthy subject group. While GGI has successfully quantified the extent of gait abnormality of Parkinson's [31] or cerebral palsy [28] patients compared to normal subjects, GGI has not been used to quantify a single subject's abnormal gait compared to his/her normal gait to capture the moment when hazards affect his/her gait pattern. Furthermore, GGI requires a total of 16 gait features to compute, which makes GGI hard to apply in a dynamic construction environment.

To respond to the need for such a gait abnormality assessment tool for construction workers, we used WIMU data to develop the IMU based Gait Abnormality Score (I-GAS) to measure the deviation of a single subject's momentary gait stride (i.e., hazard) from his/her normal gait strides. We used the Mahalanobis Distance (MD) to measure the abnormality (i.e., deviations) of gait between normal and hazard. The MD is a distance measurement method that measures the distance between a sample point and group of reference samples while simultaneously considering the distribution of reference samples [33]; this measure is widely used in multivariate outlier detection and clustering algorithms.

Thanks to MD, the correlation between computed gait features can be removed, and measurement unit difference between gait features can also be removed since MD rescales each feature to have unit variance. This paper calculated the I-GAS using Equation 7.

$$I\text{-}GAS = \sqrt{(x-\bar{y})C^{-1}(x-\bar{y})^{T}} \tag{7}$$

where, x is an (N x M) vector of the number of observation samples (N) and computed gait features (M), y is a (K x M) vector of number of reference samples (K) and computed gait features (M), $\bar{y}$ is a (1 x M) vector of mean value of reference data (y), and C^{-1} is the inverse covariance matrix of reference data (y).

This paper investigates the usefulness of I-GAS in estimating the existence and the location of a hazard in laboratory experiments.

3.3 Laboratory Experiments

The laboratory experiments involving four humans were designed and conducted to collect subjects' gait data while they were simulating movements of ironworkers on a skeletal steel beam. To accomplish this task, we constructed a 24.4 m (80 feet) long steel beam 10 cm off the ground. Subjects were asked to walkover its surface (15 cm width) at the typical speeds for eight times. To have the same length of walk distance between experiment trials, walking start-point and end-point are assigned by the experiment organizer at the 1.5m (5 feet) and 22.9 m (75 feet). The experiment included either an obstacle (experiment #2 and #3) or a slippery surface (experiment #4 and #5) surface at varying locations on the steel beam to represent hazards that could cause slips and trips (or possibly falls). To have gait data which is not influenced by hazard as a reference for abnormality measure, all subjects also asked to walk on the beam without any installed hazard, called as "normal gait" in this study (See Table 1).

Table 1. Detail of laboratory experiments

Number	Hazard Types	Hazard Location	IMU	Time
1	-	-	Ankle	5 min
2	Obstacle	9.1 m (30 feet)	Ankle	5 min
3	Obstacle	15.2 m (50 feet)	Ankle	5 min
4	Slippery	9.1 m (30 feet)	Ankle	5 min
5	Slippery	15.2 m (50 feet)	Ankle	5 min

For the obstacle, this study installed wood block which has 76 cm (30-inch) length and 10 cm (4-inch) height on the I-beam. The slippery surface was installed to cover 152 cm (60-inch) length of the I-beam and by using liquid (oil) on the plastic. During experiment, all of the subjects were asked to wear a safety harness, a safety hat, and safety boots (See Figure 4).

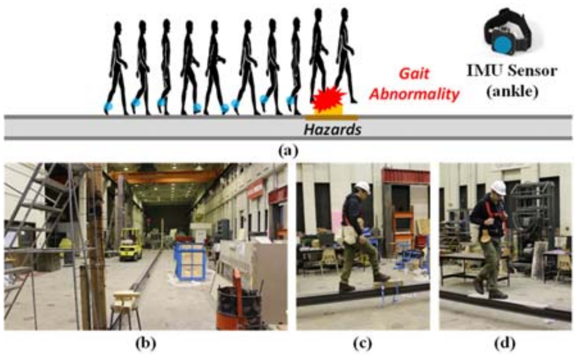

Figure 4. (a) Concept of hazard identification using WIMUs, (b) laboratory experiment environment, (c) obstacle on I-beam, and (d) slippery surface on I-beam

Experiment subjects walked continuously on the steel I-beam (return at the end point). During experiments, a WIMU (Opal, APDM Inc.) was attached to the right ankle of subjects to collect kinematic data. Three axes of acceleration (m/s2), angular velocity (rad/s), and magnetic field (uT) were obtained at a sampling frequency of 128 Hz. The quaternion rotation information of the object was acquired from the WIMU, which used the methodology of Bertrand et al. [24]. In addition to the WIMU, video cameras recorded data about all experiment procedures; these video data were synchronized to have the same timestamp with the WIMU data. These video data were used as a ground truth to identify the gait cycles which are influenced by installed hazards. In general, if there is any overlap between the stride distance of a gait cycle and the boundary of an installed hazard, that gait cycles are considered to include the interaction with the hazard. One to three consecutive gait cycles were thus classified as interacting with each installed hazard.

4 Results and Discussion

4.1 Gait Feature Computations

Gait features were computed using data collected from WIMUs for workers in both normal and hazardous conditions. Figure 5 illustrates the distributions of gait features for two subjects walking without a hazard present (*No Hazard*), walking over an obstacle (*Obstacle*), and walking on a slippery surface (*Slippery Surface*). Hazards caused a certain level of disruptions to gait features (e.g., Figure 5-e and 5-f), a fact that demonstrates the possibility of identifying hazards using worker's gait disruptions. The analysis of the aggregated data from all of the subjects also confirmed that the hazards caused significant differences ($p<0.05$) in several gait feature values.

However, the results also confirmed that such disruptions caused by the hazards varied by subjects and by gait features. For example, the slippery surface caused a change in Subject 1's stride distance (Figure 5-d) but did not create any noticeable change in Subject 2's stride distance (Figure 5-c). The analysis of the aggregated data from all of the subjects confirmed such uncertainty in the effects of hazards on individual gait features; it found that the stride distance at the aggregated data level was susceptible only to the slippery surface, not to the obstacle. These findings demonstrate the need for I-GAS to evaluate anomalies of multiple gait features in a comprehensive way.

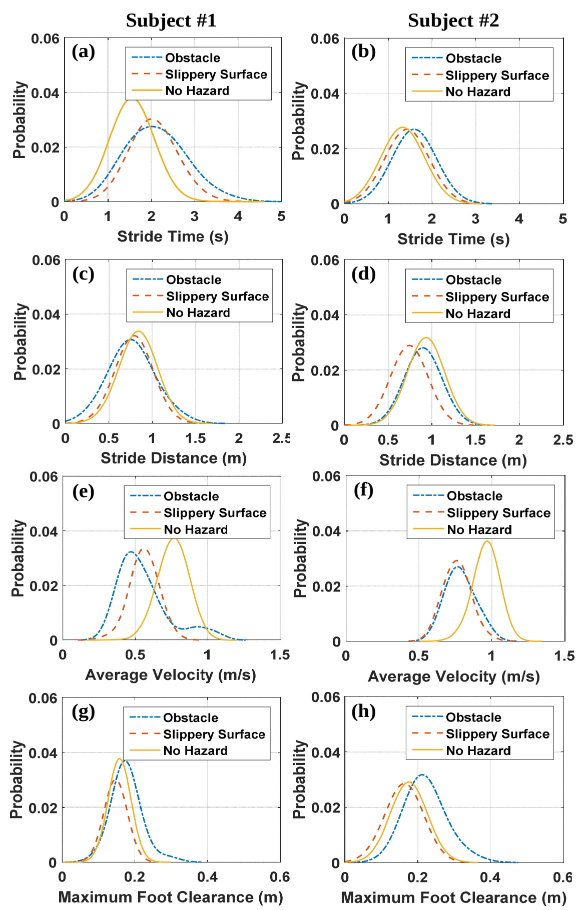

Figure 5. Results of the probability distribution for the computed gait features of Subject #1 and #2: (a, b) stride time; (c, d) stride distance; (e, f) average velocity; and (g, h) maximum foot clearance

4.2 WIMU-based Gait Abnormality Score Computations

Figure 6 shows the distributions of the subjects' combined I-GAS values for the *No Hazard, Obstacle,* and *Slippery Surface* trials (see Figure 6). The results show a clear difference in the I-GAS distributions for hazard and no-hazard conditions, and they demonstrate the usefulness of using IGAS in identifying hazard conditions.

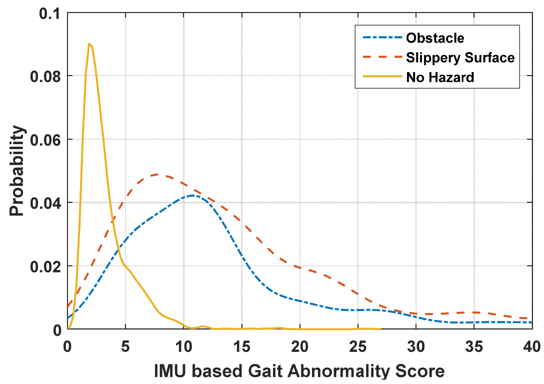

Figure 6. Probability distribution of the subjects' combined I-GAS.

Figure 7 illustrates an experimental application of the I-GAS to identify hazards. The I-GAS value of each gait cycle was mapped on the experimental site according to its estimated location—the location of a gait cycle was determined based on the stride lengths of previous gait cycles. Figure 7-a presents the mapped I-GAS values for individual subjects. The hazard location (at around 15.2 m) has a high I-GAS value, which demonstrates the success of the score at identifying hazards. However, similarly high values are also found in other, no-hazard locations. These noisy values illustrate that subjects continue to change their gait patterns even in no-hazard conditions.

Aggregation of the I-GAS values from multiple subjects (see Figure 7-b) helped filter out such noise. In particular, more samples (e.g., I-GAS values from multiple trials of multiple subjects) help to distinguish hazardous conditions more clearly. To this end, analyzing the collective gait patterns of multiple workers would be necessary to effectively identify hazards in a dynamic construction environment. Future research needs to investigate an efficient way to reveal these hazards with lower data requirements.

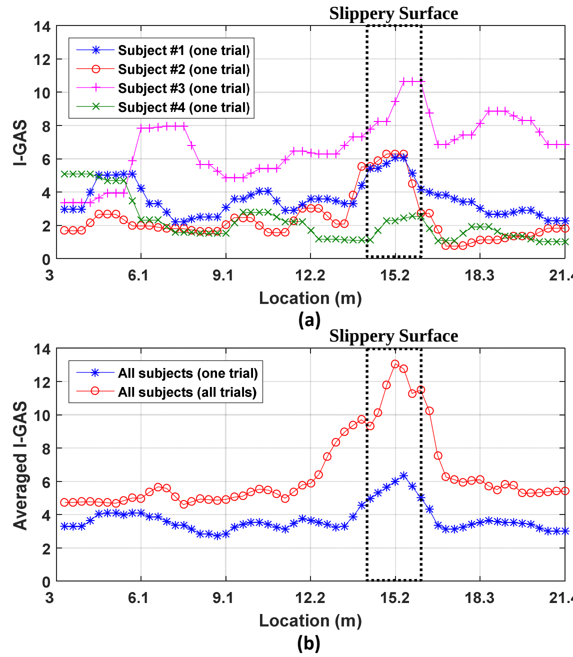

Figure 7. Preliminary results of hazard identification (experiment #5) using I-GAS: (a) I-GAS values from one trial with individual subjects, (b) averaged I-GAS values from one/all trials with all subjects

5 Conclusion

This study investigates the usefulness of gait analysis in identifying safety hazards. Using gait features that were estimated using WIMU data, this study developed the I-GAS to quantify the abnormality of each stride compared to normal strides at an individual level. Laboratory experiment settings that simulated steel connection tasks demonstrated the usefulness of the I-GAS in identifying two types of fall hazards (i.e., obstacles and slippery surfaces). Considering the possibility of ambulatory gait monitoring with WIMUs, the presented approach could help identify various types of fall hazards that cause disruptions in workers' gait and balance.

Our future research will look into the difference in gait features and the I-GAS values between individual workers and will study aggregation methods to evaluate the collective gait abnormality from multiple workers. Also, different types of possible hazards or hidden hazards will be studied to test the developed I-GAS-based technique for automated hazard identification.

Acknowledgement

The authors would like to acknowledge the excellent support and technical assistance from Cory Lyons— Project manager, Davis Erection Co Inc. (Topping Out Inc.) of Lincoln, NE— and Dr. Terry Stentz— Associate Professor, Durham School of Architectural Engineering and Construction, UNL— in designing and conducting the experiment. This study was financially supported by the Nebraska Research Initiative and National Science Foundation grant CIS #1538029 and CNS #1423379. Any opinions, findings, conclusions, or recommendations expressed in this article are those of the authors and do not necessarily reflect the views of the Nebraska Research Initiative and National Science Foundation.

References

[1] G. Carter, S. Smith, Safety Hazard Identification on Construction Projects, Journal of Construction Engineering and Management. 132 (2006) 197–205.

[2] D.L. Goetsch, Occupational Safety and Health in the Age of High Technology : For Technologists, Engineers, and Managers, Prentice Hall, Eaglewood Clifts, New Jersey, 1996.

[3] A. Albert, M.R. Hallowell, B.M. Kleiner, Experimental field testing of a real-time construction hazard identification and transmission technique, Construction Management and Economics. 32 (2014) 1000–1016.

[4] S. Bahn, Workplace hazard identification and management: The case of an underground mining operation, Safety Science. 57 (2013) 129–137.

[5] A. Albert, M. Hallowell, B. Kleiner, Enhancing Construction Hazard Recognition and Communication with Energy-Based Cognitive Mnemonics and Safety Meeting Maturity Model: Multiple Baseline Study, Journal of Construction Engineering and Management. 140 (2014)

[6] H.J. Lipscomb, J.E. Glazner, J. Bondy, K. Guarini, D. Lezotte, Injuries from slips and trips in construction, Applied Ergonomics. 37 (2006) 267–274.

[7] S. Han, S. Lee, A vision-based motion capture and recognition framework for behavior-based safety management, Automation in Construction. 35 (2013) 131–141.

[8] Hardhat-Wearing Detection for Enhancing On-Site Safety of Construction Workers, Journal of Construction Engineering and Management. 141 (2015) 04015024.

[9] T. Cheng, G. Migliaccio, J. Teizer, U. Gatti, Data Fusion of Real-Time Location Sensing and Physiological Status Monitoring for Ergonomics Analysis of Construction Workers, Journal of Computing in Civil Engineering. 27 (2013) 320–335.

[10] U. Gatti, G. Migliaccio, S. Schneider, Wearable Physiological Status Monitors for Measuring and Evaluating Workers' Physical Strain: Preliminary Validation, in: Computing in Civil Engineering (2011), American Society of Civil Engineers, n.d.: pp. 194–201. http://ascelibrary.org/doi/abs/10.1061/41182%28416%2924 (accessed March 11, 2014).

[11] U.C. Gatti, S. Schneider, G.C. Migliaccio, Physiological condition monitoring of construction workers, Automation in Construction. 44 (2014) 227–233.

[12] L. Joshua, K. Varghese, Accelerometer-Based Activity Recognition in Construction, Journal of Computing in Civil Engineering. 25 (2011) 370–379.

[13] K. Yang, S. Aria, T.L. Stentz, C.R. Ahn, Automated Detection of Near-miss Fall Incidents in Iron Workers Using Inertial Measurement Units, in: Construction Research Congress 2014, American Society of Civil Engineers, 2014: pp. 935–944. http://ascelibrary.org/doi/abs/10.1061/9780784413517.096 (accessed August 22, 2014).

[14] K. Yang, H. Jebelli, C.R. Ahn, M.C. Vuran, Threshold-Based Approach to Detect Near-Miss Falls of Iron Workers Using Inertial Measurement Units, in: Computing in Civil Engineering 2015, American Society of Civil Engineers, 2015: pp. 148–155. http://ascelibrary.org/doi/abs/10.1061/9780784479247.019 (accessed April 4, 2016).

[15] V.V. Khanzode, J. Maiti, P.K. Ray, Occupational injury and accident research: A comprehensive review, Safety Science. 50 (2012) 1355–1367.

[16] L.M. Schutte, U. Narayanan, J.L. Stout, P. Selber, J.R. Gage, M.H. Schwartz, An index for quantifying deviations from normal gait, Gait Posture. 11 (2000) 25–31.

[17] T.A. Wren, K.P. Do, R. Hara, F.J. Dorey, R.M. Kay, N.Y. Otsuka, Gillette Gait Index as a gait analysis summary measure: comparison with qualitative visual assessments of overall gait, Journal of Pediatric Orthopaedics. 27 (2007) 765–768.

[18] M.O. Derawi, Accelerometer-based gait analysis, a survey, Nor Informasjonssikkerhetskonferanse NISK. (2010).

[19] A. Muro-de-la-Herran, B. Garcia-Zapirain, A. Mendez-Zorrilla, Gait Analysis Methods: An Overview of Wearable and Non-Wearable Systems, Highlighting Clinical Applications, Sensors. 14 (2014) 3362–3394.

[20] S.R. Hundza, W.R. Hook, C.R. Harris, S.V. Mahajan, P.A. Leslie, C.A. Spani, L.G. Spalteholz,

B.J. Birch, D.T. Commandeur, N.J. Livingston, Accurate and reliable gait cycle detection in Parkinson's disease, Neural Systems and Rehabilitation Engineering, IEEE Transactions on. 22 (2014) 127–137.

[21] N. Kitagawa, N. Ogihara, Estimation of foot trajectory during human walking by a wearable Inertial Measurement Unit mounted to the foot, Gait & Posture. (2016).

[22] S.J.M. Bamberg, A.Y. Benbasat, D.M. Scarborough, D.E. Krebs, J.A. Paradiso, Gait Analysis Using a Shoe-Integrated Wireless Sensor System, IEEE Transactions on Information Technology in Biomedicine. 12 (2008) 413–423.

[23] M. Chen, B. Huang, Y. Xu, Intelligent shoes for abnormal gait detection, in: IEEE International Conference on Robotics and Automation, 2008. ICRA 2008, 2008: pp. 2019–2024.

[24] P.J. Bertrand, A. Anderson, A. Hilbert, D.J. Newman, Feasibility of Spacesuit Kinematics and Human-Suit Interactions, 44th International Conference on Environmental Systems, 2014. https://repositories.tdl.org/ttu-ir/handle/2346/59680 (accessed September 21, 2015).

[25] M.W. Whittle, Gait analysis: an introduction, Butterworth-Heinemann, 2014.

[26] S.-W. Lee, K. Mase, K. Kogure, Detection of spatio-temporal gait parameters by using wearable motion sensors, in: IEEE, 2006: pp. 6836–6839.

[27] K. Aminian, B. Najafi, C. Büla, P.-F. Leyvraz, P. Robert, Spatio-temporal parameters of gait measured by an ambulatory system using miniature gyroscopes, Journal of Biomechanics. 35 (2002) 689–699.

[28] A.M. Sabatini, C. Martelloni, S. Scapellato, F. Cavallo, Assessment of walking features from foot inertial sensing, IEEE Transactions on Biomedical Engineering. 52 (2005) 486–494.

[29] J.C. Alvarez, D. Alvarez, A. López, R.C. González, Pedestrian Navigation Based on a Waist-Worn Inertial Sensor, Sensors. 12 (2012) 10536–10549.

[30] A.R. Jimenez, F. Seco, C. Prieto, J. Guevara, A comparison of Pedestrian Dead-Reckoning algorithms using a low-cost MEMS IMU, in: IEEE International Symposium on Intelligent Signal Processing, 2009. WISP 2009, 2009: pp. 37–42.

[31] M. Galli, V. Cimolin, M.F.D. Pandis, M.H. Schwartz, G. Albertini, Use of the Gait Deviation Index for the Evaluation of Patients With Parkinson's Disease, Journal of Motor Behavior. 44 (2012) 161–167.

[32] M.H. Schwartz, A. Rozumalski, The gait deviation index: A new comprehensive index of gait pathology, Gait & Posture. 28 (2008) 351–357.

[33] R. De Maesschalck, D. Jouan-Rimbaud, D.L. Massart, The Mahalanobis distance, Chemometrics and Intelligent Laboratory Systems. 50 (2000) 1–18.