Machine Learning for Assessing Real-Time Safety Conditions of Scaffolds

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Abstract –

Researchers have taken advantage of technological advancements to automate construction processes; as a result, significant progress has been made in designing and planning temporary structures. Despite this effort, relatively little attention has been placed on automating the monitoring of safety issues of scaffolding structures, which are one of the major elements used in the construction industry. A need has emerged for a reliable means to assess the safety conditions of scaffoldings. This paper proposes a method of integrating strain-gage sensing with a machine-learning algorithm (support vector machine) to assess the real-time safety conditions of scaffolds. Based on actual strain data of scaffolding members, which were collected using wireless sensors for various loading cases on the scaffolding structure, a support vector machine was applied to differentiate the scaffolding conditions into 'safe', 'overturning', 'uneven settlement', or 'overloading' conditions. Such an automated differentiation of the condition of a scaffold could help to determine whether or not the scaffolding is safe to use without deploying safety inspectors throughout the site. The proposed method was experimentally validated to be successful in estimating the safety condition of a scaffold with an average accuracy of 97.66% for the cases that were tested. The proposed methodology could serve as a real-time monitoring system to determine the status of scaffolding structures. Its application is expected to significantly improve reliability in assessing the safety conditions of scaffolding structures, compared to conventional safety inspections, and to resolve the related safety issues.

Keywords –

Scaffolding, real-time monitoring, strain sensor, machine learning, safety, condition assessment, support vector machine

1 Introduction

Over last several years, interest about information and sensing technologies and their potential in applications has spread across the construction industry, and has resulted in research on automation during various aspects of construction, including design and planning as well as construction operation and management. Researchers [1,2] initiated the Building Information Modelling (BIM) Safety project to uncover potential opportunities using BIM to advance construction safety in planning. In addition, other studies [3,4] have incorporated BIM in scaffolding structures for scheduling and planning purposes [3,4].

While past research has identified new ways to use various resources to plan for safety, in reality, the construction industry still suffers from catastrophic events on a regular basis. To name a few large and deadly accidents, in 2002, the collapse of a scaffold at the Jon Hancock Center in Chicago killed three people and injured a number of people [5]. A recent scaffold collapsed in Houston in 2015, trapping six workers under piles of rubble until they were rescued; in this case, several citations were issued to the associated companies for not properly initiating and maintaining the safety of the scaffolds [6]. Many research articles [7-10] have discussed the problems in using manual inspections, which site managers are required to conduct, including ineffectiveness, unreliability, time consumption, and high cost. Given inadequate practices used currently and the past accidents, it is evident that safety issues of scaffolds during construction activities present challenges to the industry. It also is evident that there is an urgent need for an advanced method for safeguarding scaffolding.

The application of structural analysis in understanding the real time safety condition of a scaffold is an option for safeguarding scaffolding. However, structural analysis requires a full mathematical structural model and actual loading in each of the scaffold members for detailed analysis. However, in real time at construction sites, it is difficult to acquire all this information. Hence, this method may not be suitable for assessing the real-time safety of the scaffold as desired in construction sites. While, with a sufficient number of training data, the implementation of machine learning (ML) can address the limitations found in structural analysis as ML requires only a set of strain data from the strain sensors to predict the real-time stability condition of the scaffold. Thus, a ML approach has been implemented in the proposed methodology. As the structural conditions can be classified to specific categories, we selected SVM as a supervised ML approach.

The objective of this research was to develop an integrated method for assessing the structural safety conditions of a scaffold by using 1) strain sensors to collect real-time strain measurements from scaffolding structures and 2) applying a supervised machine-learning technique (support vector machine) to the strain data in order to analyze the safety conditions automatically of scaffolding structures.

2 Recent Research on Advanced Information and Sensing Technologies

Many researchers explored sensing technologies to assist in construction operation and management. Motion sensors [11,12]; radio-frequency identification (RFID) [13–15]; and ultra-wideband (UWB) [16–19], Bluetooth [20,21], vision [22–24], and laser [25–27] technologies have been studied extensively to discover advanced ways to collect and analyze data. Most of the safety applications from such research, however, are limited to directly using site data from deployed sensors. On-and-off-based violation detection is an example of the direct use of sensory data. Other studies have investigated methods of collecting data on safety issues, but those efforts were limited to handling safety issues directly.

To assist decision making regarding safety, a few researchers [28-30] have integrated sensing technology with machine-learning techniques. This advanced technique allows safety challenges associated with repeated actions to be captured automatically by the system. Researchers have also automated safety monitoring by integrating site information for various construction activities into the construction schedule [31-32]. As far as scaffolding safety is concerned, a minimal level of research has been conducted, with limitations. Moon et al. [33] installed a network of sensors to analyze the condition of a scaffold by using multiple types of sensors, such as an inclinometer as well as ultrasonic and strain gages. Yuan et al. [34] developed a new system, called the Cyber-Physical System (CPS) that links a virtual model of a scaffold with a sensor-based monitoring system. Despite the advancements that these researchers have made, the strain patterns based on structural responses have not been investigated properly, which can offer the potential for rigorous analysis. By applying machine-learning techniques, such patterns could be parameterized and used for analyzing the safety conditions of a structure (e.g., scaffolding).

3 Approach

Figure 1 shows the flowchart of the approach used in this research. It involves six stages, including the construction of a database for structural analysis, process of learning the training data, and the prediction of the conditions of a scaffold. Steps 1-4 pertain to the development of a database system for learning, and Steps 5-6 pertain to the prediction of safety assessments when using real scaffolding structures and strain sensors (CFLA-3-350).

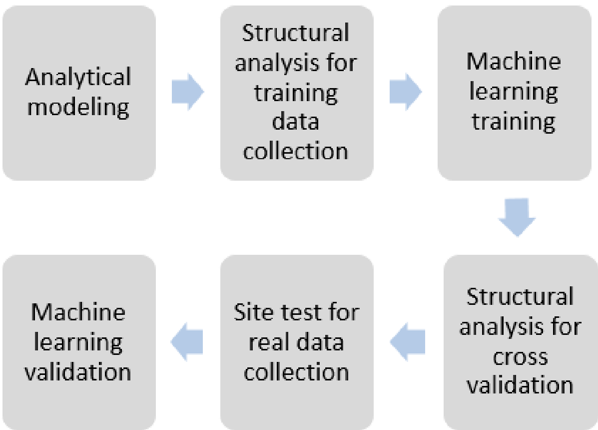

Figure 1 Flowchart of the proposed approach for safety monitoring of a scaffold based on machine learning

To conduct a structural analysis for safety assessment:

Step 1: First, we modelled a scaffolding structure.

Step 2: Then, the constructed structural model was analyzed by using various loading cases.

Step 3: The results of each of the cases were loaded into a database for the learning process.

Step 4: Then, the learning parameters of a machine-learning algorithm, support vector machine (SVM) in this research, were obtained such that the cross-validation produced reliable results, that is, over 95% accuracy.

Step 5: As the real-time strain data were collected, SVM was applied to implement automated analysis by predicting the safety state based on the trained data sets and associated learning parameters

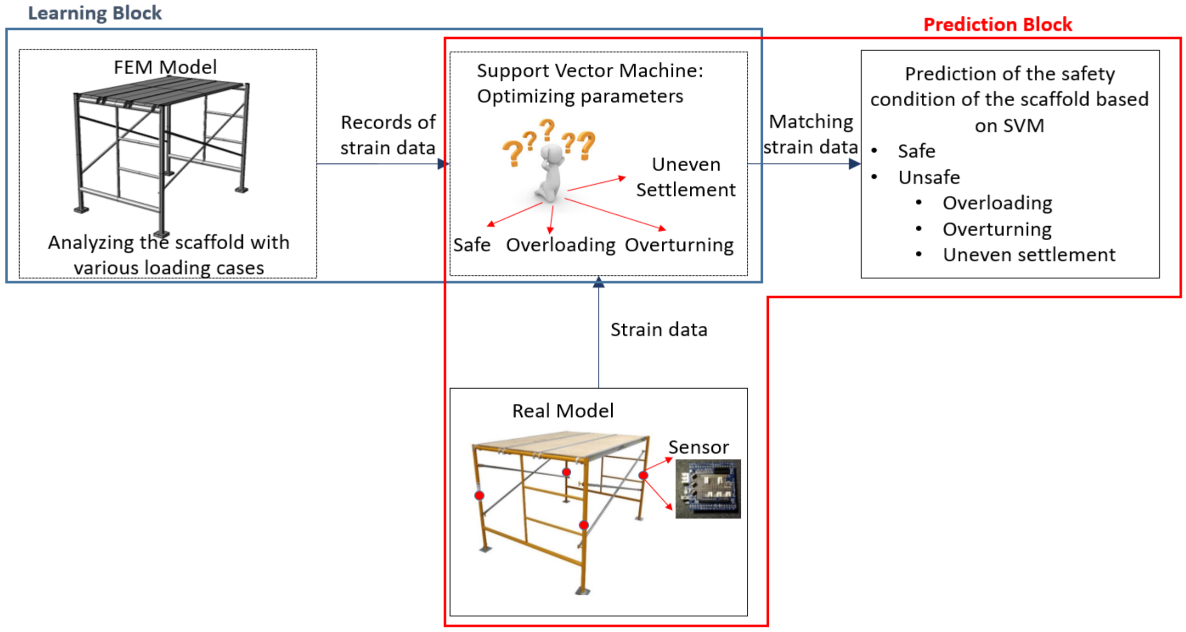

Figure 2 Framework of the approach, with four categories for safety assessment

Figure 2 elaborates the process of the proposed monitoring method and the relationship among the analytical model, analytical data, real model, real data, and encompassing machine-learning algorithm. Figure 2 shows the four categories of safety conditions that were possible as a result of loading conditions on a scaffold; safe, overloading, overturning, and uneven settlement. The SVM-based assessment analyzed the safety conditions of the scaffold with respect to these four categories.

3.1 Learning Part 1: Pre-Processing for the Generation of Training Data

One of the most important steps for machine-learning approaches is the generation of enough numbers for the training data, because the learning algorithms and their optimized parameters heavily rely on the availability of training data on which predictions are based that are used in decision making. Using a finite element model analysis, 300 data sets were generated for each of the four categories (1,200 strain-load data sets). Table 1 shows a sample of the training data sets, with four data sets for each category.

The loading was based on the four safety categories, and the strain data was collected from the four locations shown in Figure 2, based only on the elastic deformation of structure. Due to safety reasons, the tests were controlled to be safe with the following cases:

- Safe: we limited the weight to 400 kgf although the OSHA standard was 1229 kgf for the size of the tested scaffold; a heavy-duty scaffolding should not exceed 75 pounds per square foot applied uniformly over the span area [35].
- Overloading: we considered any weight beyond 400 kgf as overloading
- Overturning: to emulate the effect of overturning, we used a forklift to lift two columns by less than two inches
- Uneven Settle: to emulate the effect of ground settlement, we used a forklift to lift one column by less than two inches

Table 1 Sample of the training data sets

Category	Strain 1 (με)	Strain 2 (με)	Strain 3 (με)	Strain 4 (με)
Safe	-37.69	-48.07	-33.05	-50.81
Safe	-49.26	-54.51	-45.35	-52.28
Safe	-60.46	-54.37	-57.06	-52.07
Safe	-55.40	-42.07	-16.39	-33.73
Overturning	12.29	-5.33	-17.36	0.24
Overturning	1.97	-5.31	-3.01	10.67
Overturning	16.69	6.12	-0.20	14.22
Overturning	1.47	-7.01	2.67	11.78
Overloading	-71.81	-47.46	-47.22	-53.17
Overloading	-59.43	-52.97	-68.76	-54.25
Overloading	-75.59	-62.33	-37.29	-61.37
Overloading	-51.43	-46.94	-62.33	-74.08
Uneven Settle	-17.72	5.91	2.99	-15.95
Uneven Settle	-8.83	0.65	5.57	-9.95
Uneven Settle	-14.98	6.11	0.05	-22.08
Uneven Settle	-24.75	-8.96	8.77	-3.33

The four categories represented different aspects of the structural behavior of a scaffold, and each behavior was indicated by the analyzed strain values corresponding to one of the categories.

3.2 Learning Part 2: Pre-Processing for Training with a Support Vector Machine

This research used one of well-known machine-learning techniques, a support vector machine, to train the data sets that represented the pre-processed load-and-strain values. The load-related strain data (inputs) were processed by SVM to train SVM classifiers (outputs) with the four categories (i.e., safe, overloading, overloading, and uneven settlement). SVM is a binary classification technique that formulates a plane to separate the data into two groups:

$$f^{(i)}(x) = \boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{x}^{(i)} + b = 0, \tag{1}$$

where $x^{(i)}$ is the feature vector at the i^{th} order, and $\boldsymbol{\omega}$ and b are updating parameters. Then, the classification was made by plugging the function, f(x), into a sigmoid function as shown:

$$h(x^{(i)}) = g(\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{x}^{(i)} + b) = \frac{1}{1+e^{-(\omega^{\mathrm{T}}x^{(i)}+b)}}, \tag{2}$$

where g is a sigmoid function. Because the outputs of a sigmoid function range from 0 to 1, a classifier function can be applied with two labels (i.e. $\mathrm{y}^{(i)} \in \{1, -1\}$), as shown:

$$\mathrm{y}^{(i)} = \begin{cases} 1 \ \ if\ h(x^{(i)}) \geq 0.5 \\ -1\ if\ h(x^{(i)}) < 0.5 \end{cases}, \tag{3}$$

As the data sets are classified by a plane, each classified set is separated by a margin, and the functional margin is defined as:

$$\mathrm{r}^{(i)} = \mathrm{y}^{(i)}(\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{x}^{(i)} + b). \tag{4}$$

The maximum margin classifier that is the key step for parameter optimization is expressed as:

$$\max_{r,\omega,\mathrm{b}} \frac{r}{\|\omega\|_2} \quad \text{such that } \mathrm{y}^{(i)}(\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{x}^{(i)} + b) \geq r,\ for\ all\ data\ sets\ i. \tag{5}$$

As the value of r can be set to a constant, and because it only scales the values of the updating parameters, Eq. 5 can be simplified further to:

$$\min_{\boldsymbol{\omega},\mathrm{b}} \|\boldsymbol{\omega}\|_2 \quad \text{such that } \mathrm{y}^{(i)}(\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{x}^{(i)} + b) \geq 1,\ for\ all\ data\ sets\ i. \tag{6}$$

For a more sophisticated classification, we used the Gaussian kernel method:

$$K(\boldsymbol{x}^{(i)}, \boldsymbol{x}^{(j)}) = \exp\left(-\frac{\|x^{(i)} - x^{(j)}\|_2^2}{2\sigma}\right) \tag{7}$$

The corresponding change in the classification function is:

$$\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{x}^{(j)} + b = \sum_{all\ i} w_i K(x^{(j)} x^{(i)}) + \mathrm{b} \tag{8}$$

Using these equations for a binary classifier, one category can be classified. To further classify more categories (e.g., four categories), the one-versus-all (OVA) method [36] was applied to all the training data sets; accordingly, we extracted the optimized parameters for each of the four categories. Figure 3 illustrates a conceptual example with four classifiers defined by the optimized parameters and four cases classified by the classifiers.

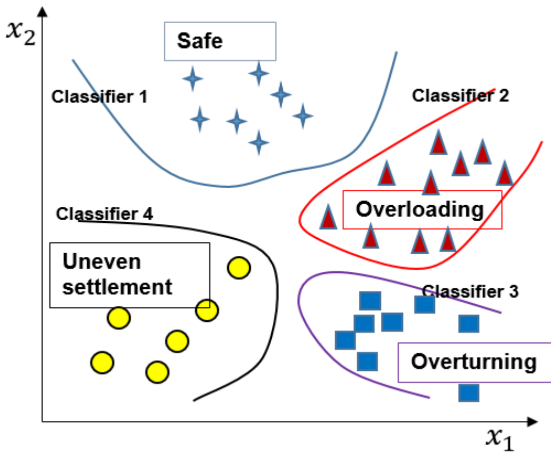

Figure 3 Classification with four classifiers

3.3 Prediction: Real-Time Data Collection and Estimation of the Safety Conditions

As the parameters for the four classifiers became available after the learning step, real-time strain data from an actual scaffold were processed by SVM to predict the safety conditions of a scaffold. To collect such strain data, this research developed customized strain sensors on an Arduino platform and installed them on the four columns of the scaffold being tested. This step was straightforward because the parameters for the classifiers were available from analytical Finite Element Method (FEM) solutions to the load-strain relationship and also because the actual strain data could be collected by strain

Figure 4 Experimental setup with a one-bay scaffold

sensors attached to the scaffold. Actual strain data were validated with respect to the four classifiers for prediction purposes. For statistical assessment of the accuracy of the SVM used in this research, the prediction rate was computed for each of the categories:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100 \qquad (9)$$

where:

TP = true positive
TN =true negative
FP = false positive
FN =false negative

3.4 Experimental Validation

To test the proposed method of real-time assessment of the safety of a scaffolding structure, a one-bay scaffolding structure was set at an indoor site, as shown in Figure 4. The dimension of the scaffold was 213 cm (L) x 158 cm (W) x 386 cm (H); in addition, four strain sensors were attached to the four columns of the scaffold. As soon as strain data were measured and transmitted to a computer equipped with the SVM algorithm, they were analyzed to predict the safety conditions of the scaffold for given loading conditions. We purposely tested 150 cases of each of the unsafe conditions (50 trials x 3 categories), and evaluated the analyzed results compared to the actual safety conditions of the scaffold.

Table 2 shows the results of the three unsafe cases, and Table 3 shows the binary classifications (i.e., TP, TN, FP, and FN) of the predictions and the prediction rates. For the overloading test, the SVM predictions were 100% accurate. However, for the cases regarding the uneven settlement and overturning tests, few cases were encountered where the classifiers were incorrect; yet, the accuracy was 96.5% for both cases. Results for the uneven settlement cases showed that there was one case where the prediction was partially incorrect; this case showed positive results for uneven settlement and overturning, while it should have been positive for uneven settlement only. Due to this redundant classification, the total number of classified cases was 51 (47 + 4), although the number of the corresponding test case was 50. However, the overturning results suffered a different problem in that the classifier was not able to make correct predictions for five trials.

Table 2 Prediction of the Safety Conditions of the Scaffolding Using Real-Time Strain Data and SVM

Actual Conditions	Categories (SVM Outcome)			
	Safe	Overloading	Uneven Settlement	Overturning
Overloading	0	50	0	0
Uneven Settlement	0	0	47	4
Overturning	0	0	2	45

Table 3 Summary of the Binary Classifications and Prediction Rates

Actual condition	Categories (SVM outcome)				Accuracy
	Safe	Overloading	Uneven Settlement	Overturning	
Overloading	TN(50) FN(0)	TP(50) FP(0)	TN(50) FN(0)	TN(50) FN(0)	100.0%
Uneven settlement	TN(50) FN(0)	TN(50) FN(0)	TP(47) FP(3)	TN(46) FN(4)	96.5%
Overturning	TN(50) FN(0)	TN(50) FN(0)	TN(48) FN(2)	TP(45) FP(5)	96.5%

Despite these drawbacks, resulting from the SVM, the accuracy was high at 100%, 96.5%, and 96.5% for the three unsafe test categories in order of overloading, uneven settlement, and overturning. On average, the SVM classifier had 97.66% accuracy.

4 Conclusion

Researchers have used information and sensing technology to advance various aspects of operations related to temporary structures. Such endeavors have resulted in significant progress in safety design and the planning of temporary structures. However, as far as safety monitoring is concerned, the construction industry still relies on human efforts. The limited ability of people doing the safety monitory entails various challenges with respect to sporadic inspections over space and time, inconsistencies, and associated costs.

This research proposed a method to assess the safety conditions of a scaffold in real time by using real-time strain sensors and a machine-learning algorithm. For the machine-learning analysis, the research used a FEM technique to generate training data with respect to four cases (i.e., safe, overloading, overturning, and uneven settlement) and then applied real-time strain measurements from an actual scaffolding structure to the optimized (or learned) machine-learning method in order to predict the safety conditions of the scaffold. Such an automated process to evaluate the safety conditions of a scaffold could help to determine whether or not the scaffolding is safe to use without deploying safety inspectors throughout the site.

The proposed method was validated experimentally to be successful in estimating the safety condition of the scaffold, with an average accuracy of 97.66% for the cases tested. Thus, the proposed methodology demonstrated its ability to serve as a real-time monitoring system for determining the status of scaffolding structures. Its application is expected to significantly improve reliability in the assessment of safety conditions of scaffolding structures, compared to conventional safety inspections, and to resolve the related safety issues.

Although successful, this research identified challenges with using SVM. For example, SVM produced redundant classifications or else did not produce predictions (i.e., when all the classifiers did not generate any positive prediction). For the tested cases, the performance of SVM was acceptable; however, it should be further validated for a larger system, with more various loading cases and a greater number of strain sensors. We suspect that this change may negatively affect the performance of the SVM, as it will introduce more complexity in the optimization of the parameters and thus make prediction more difficult. Additionally, future study should consider more advanced machine-learning algorithms, such as neural network, which are known to manage more complex systems.

5 References

[1] Zhang S., Teizer J., Lee J.K., Eastman C.M., and Venugopal M. Building Information Modeling (BIM) and Safety: Automatic Safety Checking of Construction Models and Schedules. *Automation in Construction*, 29:183–195, 2013, doi:10.1016/j.autcon.2012.05.006.

[2] Kim K. and Teizer J. Automatic design and planning of scaffolding systems using building information modeling. *Advanced Engineering Informatics*, 28:66–80, 2014, doi:10.1016/j.aei.2013.12.002.

[3] Kim K., Cho Y.K., and Zhang S. Integrating work sequences and temporary structures into safety planning: Automated scaffolding-related safety hazard identification and prevention in BIM. *Automation in Construction*, 70:128-142, 2016, doi:10.1016/j.autcon.2016.06.012.

[4] Sulankivi K. and Kähkönen K. 4D-BIM for construction safety planning. In *Proceedings of the conference W099-Special Track 18th CIB World Building Congress,* pages 117-128, Salford, United Kingdom, 2010.

[5] Dalrymple R. John Hancock Center (Chicago) Suspended Scaffold Collapse. On-line: https://failures.wikispaces.com/John+Hancock+Center+(Chicago)+Suspended+Scaffold+Collapse,

Accessed: 07/08/2017.

[6] Chron. OSHA cites two in downtown scaffolding collapse near Minute Maid Park. On-line: http://www.chron.com/business/article/OSHA-cites-two-in-downtown-scaffolding-collapse-7232389.php, Accessed: 07/08/2017.

[7] Kropp C., Koch C., and König M. Interior construction state recognition with 4D BIM registered image sequences. Automation in Construction, 86:11–32, 2018, doi:10.1016/j.autcon.2017.10.027.

[8] Costin A., Pradhananga N., and Teizer J. Passive RFID and BIM for Real-Time Visualization and Location Tracking. In Proceedings of the Construction Research Congress, pages 169–178, 2014.

[9] Park J., Cho Y.K., and Kim K. Field Construction Management Application through Mobile BIM and Location Tracking Technology. In 33rd International Symposium on Automation and Robotics in Construction (ISARC 2016), International Association for Automation and Robotics in Construction (IAARC), Auburn, Alabama, Alabama, 2016.

[10] Wang L.C. Enhancing construction quality inspection and management using RFID technology. Automation in Constrction, 17:467–479, 2008, doi:10.1016/j.autcon.2007.08.005.

[11] Park J., Chen J., and Cho Y.K. Self-corrective knowledge-based hybrid tracking system using BIM and multimodal sensors. Advanced Enginering Informatics, 32:126–138, 2017, doi:10.1016/j.aei.2017.02.001.

[12] Yang K., Ahn C.R., Vuran M.C., and Kim H. Collective sensing of workers' gait patterns to identify fall hazards in construction. Automation in Construction, 82:166–178, 2017, doi:10.1016/j.autcon.2017.04.010.

[13] Fang Y., Cho Y.K., Zhang S., and Perez E. Case Study of BIM and Cloud–Enabled Real-Time RFID Indoor Localization for Construction Management Applications. *Journal of Construction Engineering and Management*, 142 (7), 2016, doi:10.1061/(ASCE)CO.1943-7862.0001125.

[14] Park J., Marks E., Cho Y.K., and Suryanto W. Performance Test of Wireless Technologies for Personnel and Equipment Proximity Sensing in Work Zones. *Journal of Construction Engineering and Management*, 142 (1), 2015, doi:10.1061/(ASCE)CO.1943-7862.0001031.

[15] Saidi K.S., Teizer J., Franaszek M., and Lytle A.M. Static and dynamic performance evaluation of a commercially-available ultra wideband tracking system. *Automation in Construction,* 20:519–530, 2011, doi:10.1016/j.autcon.2010.11.018.

[16] Park J., Cho Y.K., and Martinez D. A BIM and UWB integrated Mobile Robot Navigation System for Indoor Position Tracking Applications. Journal of Construction Engineering and Project Management, 6 (2): 30–39, 2016.

[17] Shahi A., Aryan A., West J.S., Haas C.T., and Haas R.C.G.G. Deterioration of UWB positioning during construction. Automation in Construction, 24:72–80, 2012, doi:10.1016/j.autcon.2012.02.009.

[18] Teizer J., Lao D., and Sofer M. Rapid Automated Monitoring of Construction Site Activities Using Ultra-Wideband. In 24th International Symposium on Automation & Robotics in Construction, pages 23–28, I.I.T. Madras, 2007.

[19] Maalek R. and Sadeghpour F. Accuracy assessment of Ultra-Wide Band technology in tracking static resources in indoor construction scenarios. Automation in Construction, 30:170–183, 2013, doi:10.1016/j.autcon.2012.10.005.

[20] Park J., Yang X., Cho Y.K., and Seo J. Improving dynamic proximity sensing and processing for smart work-zone safety. Automation in Construction, 84:111–120, 2017, doi:10.1016/j.autcon.2017.08.025.

[21] Li H., Yang X., Wang F., Rose T., Chan G., and Dong S. Stochastic state sequence model to predict construction site safety states through Real-Time Location Systems. Safety Sciency, 84:78–87, 2016, doi:10.1016/j.ssci.2015.11.025.

[22] Park M.-W. and Brilakis I. Construction worker detection in video frames for initializing vision trackers. Automation in Construction, 28:15–25, 2012, doi:10.1016/j.autcon.2012.06.001.

[23] Seo J., Han S., Lee S., and Kim H. Computer vision techniques for construction safety and health monitoring. Advanced Engineering Informatics, 29:239–251, 2015, doi:10.1016/j.aei.2015.02.001.

[24] Gong J. and Caldas C.H. Computer Vision-Based Video Interpretation Model for Automated Productivity Analysis of Construction Operations. Journal of Computing in Civil Engineering, 24 (3):252–263, 2010, doi:10.1061/(ASCE)CP.1943-5487.0000027.

[25] Cho Y.K., Wang C., Gai M., and Park J.J.W. Rapid Dynamic Target Surface Modeling for Crane Operation Using Hybrid LADAR System. In Proceedings of Construction Research Congress, American Society of Civil Engineers, pages 1053–1062, 2014, doi:10.1061/9780784413517.0108.

[26] Fang Y., Cho Y.K., and Chen J. A framework for real-time pro-active safety assistance for mobile crane lifting operations. Automation in Construction, 72:367–379, 2016, doi:10.1016/j.autcon.2016.08.025.

[27] Ham Y. and Golparvar-Fard M. Rapid 3D Energy

Performance Modeling of Existing Buildings Using Thermal and Digital Imagery. In Proceedings of Construction Research Congress, ASCE, pages 991–1000, West Lafayette, IN, 2012, doi:10.1061/9780784412329.100.

[28] Yang K., Ahn C.R., Vuran M.C., and Aria S.S. Semi-supervised near-miss fall detection for ironworkers with a wearable inertial measurement unit. Automation in Construction, 68:194–202, 2015, doi:10.1016/j.autcon.2016.04.007.

[29] Fang Q., Li H., Luo X., Ding L., Luo H., Rose T.M., and An W. Detecting non-hardhat-use by a deep learning method from far-field surveillance videos. Automation in Construction, 85:1–9, 2018, doi:10.1016/j.autcon.2017.09.018.

[30] Chen J., Qiu J., and Ahn C. Construction worker's awkward posture recognition through supervised motion tensor decomposition. Automation in Construction, 77:67–81, 2017, doi:10.1016/j.autcon.2017.01.020.

[31] Navon R. and Kolton O. Model for Automated Monitoring of Fall Hazards in Building Construction. Journal of Construction Engineering and Management, 132 (7):733-740, 2006.

[32] Navon R. and Kolton O. Algorithms for Automated Monitoring and Control of Fall Hazards. Journal of Computing in Civil Engineering, 21 (1):21-28, 2007.

[33] Moon S., Choi B., and Yang B. USN-Based Data Acquisition for Increasing Safety in the Concrete Formwork Operation. Journal of Computing in Civil Engineering, 26 (3):271–281, 2012, doi:10.1061/(ASCE)CP.1943-5487.0000132.

[34] Yuan X., Anumba C.J., and Parfitt M.K. Cyber-physical systems for temporary structure monitoring. Automation in Construction, 66:1–14, 2016.

[35] Occupational Safety and Health Administration (OSHA). Scaffold Specifications - 1926 Subpart L App A. Online: https://www.osha.gov/pls/oshaweb/owadisp.show_document?p_table=STANDARDS&p_id=10917, Accessed: 09/01/2017.

[36] Vapnik V. The Nature of Statistical Learning Theory. Springer science & business media, 2013.