Identification of the Structural State in Automated Modular Construction

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Abstract –

Automated construction involves complex interactions between machines and humans. Unless all possible scenarios involving construction and equipment are carefully evaluated, it may lead to failure of the structure or may cause severe accidents. Hence monitoring of automated construction is very important and sensors should be deployed for obtaining information about the actual state of the structure and the equipment. However, interpreting data from sensors is a great challenge. In this research, a methodology has been developed for monitoring in automated construction. The overall methodology involves a combination of traditional model-based system identification and machine learning techniques. The scope of this paper is limited to the machine learning module of the methodology. The efficacy of this approach is tested and evaluated using experiments involving the construction of a steel structural frame with one storey and one bay. The construction is carried out by a top-to-bottom method. During the construction of the frame, 99 base cases of normal operations are involved. 158 base cases of possible failures have been enumerated. Failure cases involve, for example, certain lifting platforms moving faster than others, improper connections of joints, etc. Strain gauges and accelerometers are installed on the structure and the data from these sensors are used to determine possible failure scenarios. Preliminary results indicate that machine learning has good potential for identifying activities and states in automated construction.

Keywords –

Structural Monitoring, System Identification, Machine Learning, Automated Construction Monitoring

1 Introduction and Background

The construction industry is one of the oldest and biggest industries in the world. Diffusion of the latest technology is difficult in construction compared to other industries due to diverse parties and uncertainties involved in construction projects. Development of construction technologies is highly influenced by the innovative technologies in other fields. Introduction of robotics and automation in construction is inevitable due to advantages such as improvement of productivity, reliability and quality, enhancement of working conditions, safety, component standardization, workforce simplification and savings in lifecycle cost as well as labour cost [1].

Automating the construction processes involves a lot of complexities in micro-level details. Machines cannot anticipate certain conditions which may look obvious to a human being. This may lead to either failure of the structure being constructed or severe accidents or both. Hence monitoring of automated construction is of paramount importance.

2 Automated Monitoring of Construction

Sensors are widely used for automated monitoring of constructed structures as well as structures under construction. In structural health monitoring, constructed structures are measured to check for the presence of defects or reserve capacity [2]–[4]. Construction activities are being monitored for ensuring various requirements such as safety practices [5], the productivity of the workers [6] and the progress of the work [7]–[9]. Sensor-based monitoring to ensure the stability of the structure is rarely studied. Cho *et al.* used strain measurements to predict the conditions of collapse for scaffolding structures using machine learning [10]. This method requires an accurate model of the scaffolding as input, which might not be available in most of the construction sites. Other than temporary structures, there are cases of monitoring of construction of high-rise buildings. Choi *et al.* studied column shortening effects of high-rise buildings with wireless strain sensing system in real-time [11]. The sensors are embedded in the column while it is being constructed. Measurements with the sensors and transferring the measured data through a wireless sensor network are automated through this system. However, from the monitored column shortening data the managers have to take appropriate corrective actions manually.

It is evident from various examples discussed above, that conventional method of construction can be improved with an automated monitoring system. For ensuring safety and reliable operations, an automated monitoring system is a necessity for automated construction. The degree of automation which can be attained in construction depends on to the extent to which micro-activities can be automated. This also depends on how well the control information is collected and coordinated to achieve overall monitoring of the entire structure. However, Sensor-based monitoring of safety and stability of an entire structure being constructed is not well explored yet.

3 System Identification in Construction

Automated construction requires rigorous monitoring to ensure the safety and stability of the structure. Appropriate sensors at optimum locations on the system will give necessary data about the system. The main research question is: How do you make sense of data from the monitoring system to take decisions about the construction process? For this, the actual state of the structure being constructed has to be identified. This can be achieved by System Identification.

System Identification appears to be a promising methodology which can be adopted for monitoring of automated construction. This methodology is widely adopted in various fields of engineering, especially for structural health monitoring in civil engineering [12]–[15]. The measurements from already existing structures are used for assessing their condition by system identification. Various methods for identifying the state of the constructed facilities are discussed in detail in a report published by ASCE in 2011[16]. However, the possibility of applying system identification in monitoring automated construction and stability of the structure being constructed has been not explored so far. Successful interpretation of measured data is highly dependent on the measurement system as well. In order to gain maximum useful information with minimal cost, the measurement system has to be systematically designed.

Most of the well-established system identification methods in construction require models or prior information about the structure. But in ongoing construction, the structure changes continuously. In this context, a rigorous approach free of models would be much more appropriate for monitoring. Machine learning techniques which are entirely data-driven opens up a possibility here.

A machine learning technique, Support Vector Machine (SVM) is proven to be successful in solving various complex construction management problems and acts as an efficient support system for decision making[17]–[22]. With careful selection of parameters, SVM gave better identification of construction activities compared to conventional system identification methods from strain sensing data [8].

4 Objective

The overall objective of this research is to develop a framework based on system identification which can be used to monitor automated construction of a structural frame. Conventional model-based system identification methods, as well as model-free approaches based on machine learning, were explored for this task. However, this paper focuses only on a machine learning based framework for monitoring. In particular, the feasibility of using support vector classification is explored. More complex deep learning models such as convolutional neural networks will be studied in the future. The machine learning module will eventually be integrated with conventional system identification techniques in order to develop a hybrid strategy that is most effective for the task of automated construction monitoring.

5 Methodology

The methodology adopted in this research involves experiments and data analytics. A prototype of an automated construction system was developed and experiments were conducted in controlled settings.

Figure 1. The partially constructed structural frame on the automation system

The automated construction methodology adopted in this study follows a top to bottom method of construction [23]. In this method, the structural frame for the roof is constructed first and the lower part is constructed sequentially by adding one module of a column at a time, followed by the coordinated lifting of the finished structure. The advantage of this type of construction is that all the activities are performed at the ground level and heavy equipment such as tower cranes are not needed. Currently, the coordinated lifting operation is automated, whereas the connection of modules of the members is done manually. Higher levels of automation are planned for the future.

The structural frame used in this study consists of circular pipe sections with couplers as connectors (Figure 1). The scaled model of a one bay one storey structural frame has six columns (Figure 2 and 3). The automation system consists of 6 lifting machines at each column position (Figure 1). Each individual machine in the system has 2 ton lifting capacity.

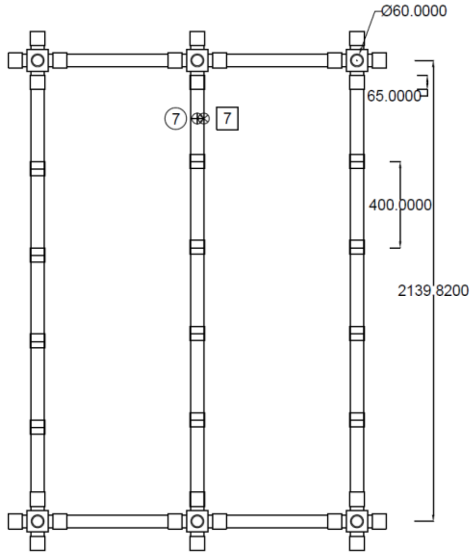

Figure 2. Front view of the structural frame with the location of sensors (All dimensions are in mm)

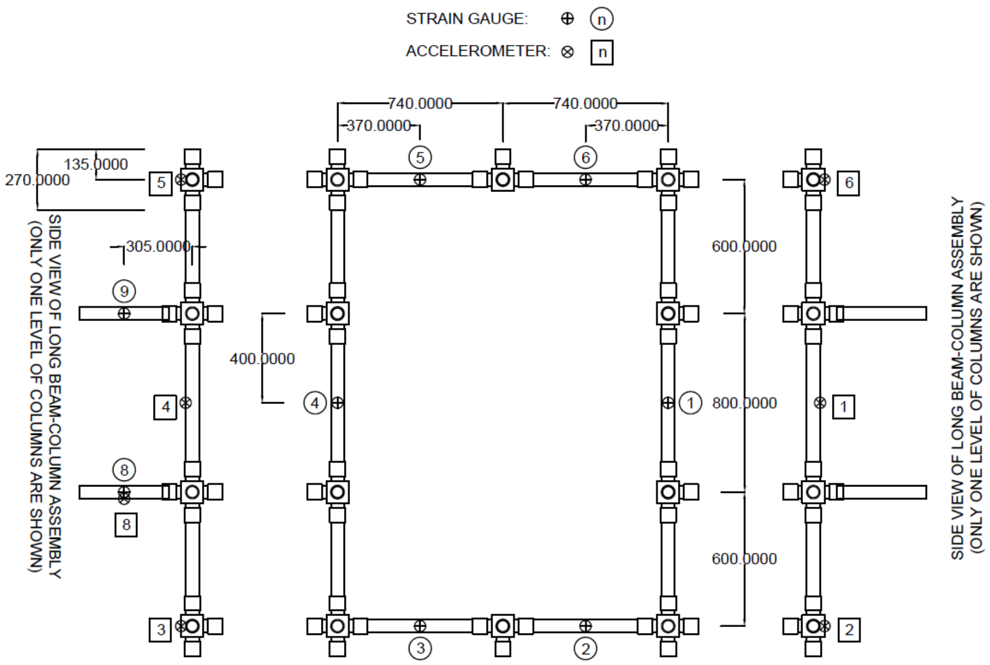

Figure 3. Plan of structural frame with the location of sensors (all dimensions are in mm)

6 SVM based framework for Monitoring Automated Construction

To monitor the state of the structure being constructed and the construction operations, a machine learning based monitoring framework is adopted in this study (Figure 4). This involves two major steps, training and predictions. During the training phase, the automated construction of the structural frame is carried out in controlled conditions within the limits of technical feasibility. Measurements from various sensors deployed in the structure are collected continuously during the automated construction process. The measured signals are analysed and features for recognising the patterns are extracted. The patterns of measurements (PTij) recorded during the tests for each combination of measurement location (i) and operating condition (j) are used to train the algorithm. This involves patterns of measurement during normal operating conditions as well as failure conditions. SVM identifies each operation state by binary classification. The data corresponds to the operation to be identified is labelled as positive class and all other operations are labelled as negative class. In linear classification, the function or discriminant which separates the classes will be a hyperplane. The equation of the discriminant is obtained by maximizing margin, which is the distance between the nearest data points from either class to the surface.

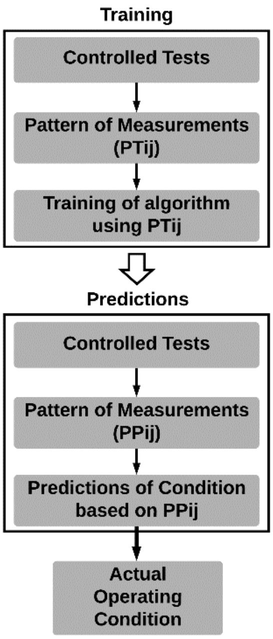

Figure 4. Machine learning based **system identification methodology**

Then controlled tests are performed and measurements are recorded (PPij). Based on the training data set, the algorithm will predict the operating condition.

7 Experimental Validation

Accelerometers (AM) and strain gauges (SG) are placed on the structure for measuring the vibration and strain during automated construction. The locations of sensors are shown in Figure 2 and 3. Totally 9 strain gauges and 8 accelerometers are deployed on the structure. 6 strain gauges are placed on the top of beam members at midspan and 3 strain gauges are placed on the top-level column modules at mid-height. 120-ohm linear strain gauges with 5 mm gauge length are used for the study. Monoaxial piezoelectric accelerometers are used for vibration monitoring. It has a measurement range of -5 g to +5 g with 1000 mv/g sensitivity. 4 out of 8 piezoelectric accelerometers are placed under the universal joints at each corner, 2 are placed under the long beams at midspan and rest of the 2 are placed on first level columns at mid-height.

First, the structure is constructed in perfect lifting conditions without errors in the assembly. Later, various failure criteria such as differential settlement and overturning are systematically introduced. Table 1 shows all the normal operating conditions and potential failure conditions involved in the construction of a one bay one storey structural frame with 5 levels of column modules. There are totally 257 cases of operation involved in constructing the structural frame in the current configuration with the automation systems developed. However, only a limited number of cases can be tested experimentally.

Considering the symmetry of the structure and practical operating conditions, the cases which have to be experimentally tested is limited to 70 without losing major details. The wired sensors are placed at the first level of the beam and column assembly in the current set of experiments. Hence connection of the beam assembly is not tested in this stage. Future experiments in which wireless communication strategy is used, the beam assembly will also be tested. While testing the failure cases, faulty conditions which will lead to potential failure of the structure during construction will be incorporated. Then the automated construction is continued and measurements will be taken. If we introduce a faulty condition, for example, an improper connection between modules of a column member, the pattern of strain and vibration will be different compared to the patterns of measurements corresponding to normal operation cycle.

The measurements taken during normal as well as failure cases will be analysed to arrive at features to train the algorithm. Each case of operation is repeated 6 times. 5 sets of data are used for training and 1 set of data is used for prediction. Starting time, ending time and duration of each operation is recorded manually in a time tracking excel sheet. Results of prediction are compared with this recorded data. The accuracy of prediction is calculated as a percentage of the total number of data points classified. Linear SVM classifier with an error penalty value 10 is used for this study.

Table 1. Total normal operating conditions and failure conditions in the automated construction

Sl. No.	Cases	Conditions of Operation	Number of Cases
	NC	Normal Operating Conditions	
1	NC1	Connection of Beam Assemblies	2
2	NC2	Coordinated Lifting of Finished Structure	7
3	NC3	Lowering of Supports	30
4	NC4	Addition of Column modules	30
5	NC5	Lifting the support until it takes the load	30
		Total Number of Normal Cases	99
	FC	Failure Conditions	
1	FC1	Non-contact of Supports after adding Column modules	30
2	FC2	Support moving faster during Co-ordinated Lifting	42
3	FC3	Improper Connection of Column modules	36
4	FC4	Improper Connection of Beam modules	40
5	FC5	Accidental Loading on the structure	10
		Total Number of Failure Cases	158
		Total Number of Cases	257

More than 50 operations are involved in the construction of a structural frame in 3 different levels of assembly by top to bottom automated construction method. This paper shows the classification of 3 different operation states. The idle state is the condition when the machine is switched on and the constructed structure is supported by all lifting supports, but no other construction activity is going on. This state gives the ambient vibration readings of the constructed structure. The normal coordinated lifting of finished structure (NC2) is the lifting of the constructed structure equally by all lifting supports for the assembly of next level of column modules beneath it. The failure condition considered is one of the supports moving faster during coordinated lifting (FC2). If this condition continues beyond a certain time, it leads to the overturning of the structure. The failure conditions are tested carefully in such a way that it will never be extended until the actual failure of the structure.

The data is acquired at a sampling frequency of 200 Hz. Millions of data points are generated from each experiment. Observing the pattern of strain and vibration measurements, average (AV) and standard deviation (SD) over moving time windows are found to be suitable features for recognizing the pattern of measured signals. In order to capture the change in pattern during sub activities, measurement data corresponds to each operation at each location is divided into 3 time windows and AV and SD are calculated for each part. These features are used to train the algorithm. Results of the study are discussed in the next section.

8 Results and Discussion

Six different parameters (3 AV values and 3 SD values) at each measurement location are used for training the algorithm. The algorithm is trained to identify three different scenarios; i) idle condition and a normal operating condition, ii) a normal operating condition and a failure condition and iii) a failure condition and idle condition. The prediction results are summarized in Table 2.

It is interesting to see that, just by using the SD of accelerometers, the algorithm can predict all operations with 100% accuracy. This will help us reduce the number of sensors used for monitoring. SD is a strong parameter for pattern recognition from vibration data. However, SD could not give good results with strain data while identifying Idle and FC2. This might be due to the small number of data points in support moving faster condition as it is a severe failure case which cannot be extended for a long-time during experiments. AV is not a reliable parameter as it might not give good results in all conditions. All the cases selected here for classification has average acceleration reading close to zero. In fact, including AV in certain cases might not even influence the prediction results.

Among the measurement type, vibration is more useful in accurate prediction. Strain data sometimes get affected by a minor level difference in the structural frame, temperature or defect in the deployment of the sensor. In terms of prediction accuracy, the best results are obtained for separation between normal and failure cases (NC2 and FC2) among all the three cases. The clearly differentiating pattern over time ensures best predictions irrespective of parameters used.

Table 2. Prediction results for normal and failure conditions. Each column reporting the percentage of accuracy corresponds to a specific combination of features and the type of measurement

Operations Classified	Percentage of accuracy						
	AV and SD of AM and SG	AV of AM and SG	SD of AM and SG	AV of AM	SD of AM	AV of SG	SD of SG
Idle and NC2	100	83.33	100	50	100	66.67	83.33
NC2 and FC2	100	100	100	50	100	100	100
Idle and FC2	100	83.33	100	50	100	66.67	66.67

9 Conclusions

Automated construction of a structure has to be monitored continuously and accurately. Sensor data have to be appropriately interpreted to take control actions during automated construction. The challenge of making sense of a large amount of sensing data can be achieved by system identification methods. These methods have been used in structural health monitoring applications. Automated monitoring of a structure using this methodology has not been explored. Most of the conventional system identification methods in construction are limited by the prior information required to apply it. Data-driven techniques in machine learning are one of the best possibilities for addressing these limitations. Machine learning techniques such as SVMs have been proven to be capable of solving complex problems in construction. However, the quality of sensor data collected drives the performance of these methods.

Results from the present study show that an SVM based framework for monitoring automated construction is feasible. In the current set of experiments, the framework has a prediction accuracy of 100% with appropriate parameters for training. Depending on the type of measurement and operation, training parameters (features) have to be selected appropriately. Standard deviations of measurement data over moving time windows have been found to be very effective in accurate prediction. Among the measurement types, vibration is found to be more useful than strains.

Research is currently in progress on the use of more sophisticated machine learning models such as convolutional neural networks. Formulation of a robust framework for automated construction monitoring which combines a conventional system identification methodology with machine learning techniques is also in progress.

Acknowledgement

Authors wish to extend their sincere gratitude to all the faculties, staff members and project interns at Structural Engineering Laboratory, Building Automation Laboratory and Civil Engineering Department Fabrication Facility, IIT Madras for their unparalleled help and support in fabrication, installation and instrumentation required for the project. The doctoral research of the first author is supported by the scholarship from the Ministry of Human Resource Development (MHRD), Government of India. The project is funded by the Department of Science and Technology (DST), Government of India through the grand DST/TSG/AMT/2015/234.

References

[1] Castro-Lacouture D. Construction Automation. In *Springer Handbook of Automation,* Nof S. Y., Ed. Springer, pages 1063–1078, 2009.

[2] Zhang Y. and Bai L. Rapid structural condition assessment using radio frequency identification (RFID) based wireless strain sensor. *Automation in*

Construction, 54:1–11, 2015.

[3] Alavi A. H., Hasni H., Lajnef N., Chatti K., and Faridazar F. An intelligent structural damage detection approach based on self-powered wireless sensor data, *Automation in Construction.*, 62:24–44, 2016.

[4] Spencer Jr B. F., Ruiz-Sandoval M., and Kurata N. Smart sensing technology for structural health monitoring. In *Proceedings of 13th World Conference on Earthquake Engineering*, Vancouver, 2004.

[5] Kim S. H., Ryu H. G., and Kang C. S., Development of an IoT-Based Construction Site Safety Management System. In *Proceedings of International Conference on Information Science and Applications*, pages 617–624, Hong Kong 2018.

[6] Aryal A., Ghahramani A., and Becerik-Gerber B. Monitoring fatigue in construction workers using physiological measurements. *Automation in Construction.*, 82:154–165, 2017.

[7] Soman R. K. *Automated Monitoring of Launching Girder Operations Using Wireless Sensor Network*. Masters Thesis, Indian Institute of Technology Madras, 2016.

[8] Harichandran A., Raphael B., and Varghese K. Inferring Construction Activities from Structural Responses Using Support Vector Machines. In *Proceedings of 35th International Symposium on Automation and Robotics in Construction (ISARC 2018),* pages 324–331, 2018.

[9] Soman R. K., Raphael B., and Varghese K. A System Identification Methodology to monitor construction activities using structural responses, *Automation in Construction*,75:79-90, 2017.

[10] Cho C., Kim K., Park J., and Cho Y. K., Data-Driven Monitoring System for Preventing the Collapse of Scaffolding Structures. *Journal of Construction Engineering and Management*, 144(8): 4018077, 2018.

[11] Choi S. W., Kim Y., Kim J. M., and Park H. S. Field monitoring of column shortenings in a high-rise building during construction, *Sensors (Switzerland)*, 13(11):14321–14338, 2013.

[12] Goulet J.-A., Texier M., Michel C., Smith I. F. C., and Chouinard L. Quantifying the Effects of Modeling Simplifications for Structural Identification of Bridges, *Journal of Bridge Engineering*, 19(1):59–71, 2014.

[13] Pasquier R., Angelo L. D., Goulet J.-A., Acevedo C., Nussbaumer A., and Smith I. F. C. Measurement, Data Interpretation, and Uncertainty Propagation for Fatigue Assessments of Structures, *Journal of Bridge Engineering*, 21(5):4015087, 2016.

[14] Pai S. G. S., Nussbaumer A., and Smith I. F. C. Comparing Structural Identification Methodologies for Fatigue Life Prediction of a Highway Bridge. *Frontiers in Built Environment*, 3:1–15, 2018.

[15] Robert-Nicoud Y., Raphael B., and Smith I. F. System Identification through Model Composition and Stochastic Search. *Journal of Computing in Civil Engineering.*19(3):239–247, 2005.

[16] Çatbaş F. N., Kijewski-Correa T., and Aktan A. E. *Structural Identification (St-Id) of Constructed Facilities.* American Society of Civil Engineers (ASCE), Structural Engineering Institute (SEI) 2011.

[17] Saitta S., Raphael B., and Smith I. F. C. Data mining techniques for improving the reliability of system identification. *Advanced Engineering Informatics*, 19(4):289–298, 2005.

[18] Lam K. C., Palaneeswaran E., and Yun Yu C. A support vector machine model for contractor prequalification. *Automation in Construction.*, 18(3):321–329, 2009.

[19] Wauters M. and Vanhoucke M. Support Vector Machine Regression for project control forecasting. *Automation in Construction*, 47:92–106, 2014.

[20] Cheng M. Y., Peng H. S., Wu Y. W., and Chen T. L. Estimate at completion for construction projects using evolutionary support vector machine inference model. *Automation in Construction.*, 19(5):619–629, 2010.

[21] Kargul A., Glaese A., Kessler S., and Günthner W. A. Heavy Equipment Demand Prediction with Support Vector Machine Regression Towards a Strategic Equipment Management. *International Journal of Structural and Civil Engineering Research*,6(2):137–143, 2017.

[22] Alwasel A., Sabet A., Nahangi M., Haas C. T., and Abdel-Rahman E., Identifying poses of safe and productive masons using machine learning. *Automation in Construction*, 84:345–355, 2017.

[23] Raphael B., Rao K. S. C., and Varghese K. Automation of modular assembly of structural frames for buildings. In *Proceedings of the 33rd International Symposium on Automation and Robotics in Construction (ISARC 2016), Auburn, USA*, pages 412–420, 2016.