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BIG VISUAL DATA ANALYSIS FOR BUILT ENVIRONMENT INFORMATION MODELING

Zhang, C.[1,2], Guo, F. [1,3], Fan, L. [1,4], and Ali, Y. [1,5]
[1] Xi'an Jiaotong-Liverpool University, China
[2] cheng.zhang@xjtlu.edu.cn, [3] fangyu.guo@xjtlu.edu.cn, [4] lei.fan@xjtlu.edu.cn, [5] y.ali18@student.xjtlu.edu.cn

Abstract: Due to the availability of large amount visual data collected, big data analysis can be used to solve engineering problems. Meanwhile, information technology is also playing an essential role in enhancing multidisciplinary solutions for more complicated problems. This paper proposes a framework of applying big visual data (BVD) into Built Environment Information Modeling (BEIM). Four tiers have been defined to provide a guideline for data collection, modelling, application and optimization. Some preliminary research work carried out by the research team is presented in the paper as well, to show the feasibility and applicability of the proposed method.

1 INTRODUCTION

Construction industry is one of the largest sectors in the world, accounts for 13% of GDP (Bilal , et al., 2016). However, evolution in this sector lags behind other economy sectors. A part of this evolution is the big data analytics technologies. Nowadays the *Big Data* concept is used for tackling complex engineering problems (Alavi & Gandomi, 2017) and noticeable transformation through different stage of civil engineering systems (e.g. design, construction, operation and maintenance) is a result of massive amount of data generated by applying testing and monitoring systems (Alavi & Gandomi, 2017). Although big data technologies have the ability to process large-scale data (Han & Golparvar-Fard, 2017), yet there is lacking in successful implementation of these technologies in current civil engineering information systems (Han & Golparvar-Fard, 2017) (Bughin, et al., 2017).

Big data is a broad term with multiple definitions but there are common characteristics. Most commonly used characteristics that define big data are volume, variety, and velocity or 3 V model (Liu, et al., 2016). Big data include all kinds of data that can be collected by different means, such as sensors, cameras, laser scanners, etc. Among those big data, visual data have better accessibility and have more impressions on human being's daily life. Recent advances in smart devices and camera-equipped platform increased the volume of visual data. In terms of cost, the large volume of visual data provides an unpresented opportunity to visually capture the actual status of the physical environment compared to other alternative methods (Han & Golparvar-Fard, 2017). The captured images and videos become useless without properly structured, organized, and localized with plan document and time. At a typical commercial building project about 95,400 images are taken by webcams, 325,000 images by professional photographers, and 2000 images by construction project team members (Han & Golparvar-Fard, 2017). The number of captured images can increase significantly with the use of unmanned ground/aerial vehicles (UGV/ UAV). This provides an unprecedented opportunity to understand the construction processes, but also requires advanced management skills and data-processing ability.

Big Visual Data (BVD) have to be characterized differently because the use of database is not directly applicable for detecting meaningful patterns out of visual data. The only way to place visual data in form of tables is to put attributes of exchangeable image file (EXIF) tags or place analyzed data (already processed) (Han & Golparvar-Fard, 2017). The existing database solution cannot capture and provide meaningful real-time querying of raw visual data. Han & Golparvar-Fard. (2017) concluded that there is not an efficient solution for dealing with a large number of visual data files. In order to utilize big visual data analytics in practice, an investigation is needed for a directory structure and visualization interface for big visual data, which will involve filtering, sorting, and storing of visual data. Also, a need for automation of the information flow at a high frequency for continuous capturing changes/data (Han & Golparvar-Fard, 2017). In the meantime, Building Information Modelling (BIM) has received a certain level of maturity in building industry, and is extended to other man-made structures, such as bridges, roads, and other infrastructures, which contributes to the entire Built Environment. Therefore, a new concept is introduced in this proposal to represent modeling the whole built environment, which we define as *Built Environment Information Modelling (BEIM)*.

2 LITERATURE REVIEW

Yang, et al. (2015) conducted a comprehensive literature review on vision-based performance monitoring. The study was divided for project level and operation level. Project level reveal performance monitoring pertaining infrastructure and building elements. Operation level performance monitoring involves tracking of onsite resources (e.g. craft workers and equipment). Omar, et al. (2018) have proposed an automatic system for monitoring construction site activities in real-time by creating 3D point cloud model (as-built) and compare it with the 3D BIM model (as-planned). The system was used to monitor reinforced concrete column. Daily photos were collected from fixed cameras installed on the construction site. In order to detect any deviation beyond the schedule four algorithms were developed. Algorithms aimed for registering 3D BIM model column surfaces, aligning the 3D point cloud with the 3D column from the BIM model, determining column point cloud and removing occlusions, and calculating the progressive column volume. Automatic notifications were sent to appropriate decision-makers if any deviation was detected. Challenging issues in the implementation of this system was related to occlusions.

Golparvar-Fard, et al. (2015) have used unordered daily construction photos to reconstruct 4D as-built point cloud model. The system represented the deviation in schedule by using color coding. Pučko, et al. (2018) have used a low precision 3D scanning device to capture workplaces and record partial point clouds. The partial point clouds were then registered and merged into a complete 4D as-built point cloud. 4D as-built BIM was constructed by identification of as-designed BIM elements within the 4D as-built point cloud. The deviation from the time schedule was obtained by comparing 4D as-built and 4D as-planned models. The differences were reported in virtual real time. Compared to other laser scanning methods, instead of periodical scanning of the whole building as-built model was continuously updated. Moreover, the used 3D scanning devices were small enough to be installed onto workers' protective helmets, neither experts' work for handling nor special maintenance were needed. Some activities of the proposed system were simulated manually, such as partial point cloud registration. Selection of correspondences was a challenge associated with the registration of an image-based point cloud and BIM.

To address this challenge, Boroujeni & Han. (2017) have presented a new localization method by detecting and matching perspectives of the image and the BIM. The average registration error between the captured image and the screenshots of the BIM was 18.4 pixel. To improve localization and registration, Boroujeni & Han. (2017) have suggested to iterate viewpoints of the BIM along the path to find the viewpoint that yields the smallest error. The results demonstrated the potential for automated alignment of an image to BIM. Furthermore, the proposed method can be used in conjunction with visual simultaneous localization and mapping (SLAM) for real time as-built modeling. Occlusions was one of the most challenging issues encountered in the implementation of visual sensors for monitoring construction site (Han, et al., 2015) (Omar, et al., 2018). Also, high Level of Development (LoD) for BIM and schedule Work-Breakdown-Structure (WBS) were required for reporting progress deviations.

To come-up these problems, Han, et al. (2015) formalized an ontology that modeled construction sequencing rationale and presented a classification mechanism that integrated this ontology with BIM to progress monitoring for partially and fully occluded components. In efforts to automate the process of modelling 3D as-built model based on geometrical continuities, Dimitrov & Golparvar-Fard. (2015) proposed new region growing method for robust context-free segmentation of unordered point clouds. Shang & Shen. (2018) have presented preliminary results of scene reconstruction on construction site with Visual SLAM and UAV. They discussed the applications of SLAM and UAV in earthwork measurement, progress management of a pavement compaction and Site asset tracking. Earth volume change was measured by comparing two SLAM models and the earth volume changes are color coded. The as-build BIM model is overlaid on the SLAM map to visualize the working progress, the current state of pavement compaction progress presented by different colours in the model.

Liu, et al. (2017) developed a method to generate a virtual construction scene by acquiring information of construction objects (e.g. the geometric information, positions, and dimension data) from on-site cameras. To avoid risk from re-planning on the actual site, the developed tool facilitated re-plan an operation in a semantic virtual construction. To monitor onsite activities by video camera network, two or more cameras might capture construction resources (e.g. equipment and worker) in the same time. This led to the repetitive counting, and resulted in inaccurate analysis of the utilization of the onsite resources. To address this issue, Zhang, et al. (2018) have proposed a matching method by identification of onsite resources through visual detection. It is worth to mention that the cameras used in the proposed method did not require to be the same type. The matching accuracy was slightly affected by lighting and weather conditions. The ability of the proposed method was limited to match construction onsite resources between two camera views.

Hamledari, et al. (2017) developed a method to automatically update industry foundation classes (IFC) based on 4D BIM model and onsite image. Hamledari, et al. (2017) present a computer vision-based algorithm able to automatically detects the components of an interior partition. For safety on construction site, Kim, et al., (2018) present an Unmanned Aerial Vehicle (UAV)-assisted visual monitoring method that can automatically measure proximities among construction resources (i.e., excavator, worker, and wheel loader). They applied A deep neural network (DNN) to object localization. The method has not yet reached the capability to be used for onsite proximity monitoring, however it has shown Promising results of visual localization and distance measurement on an image. Civil infrastructure has gained increasing interest in computer vision-based application. Seoa, et al. (2018) investigate the capabilities of UAV to conduct a bridge inspection. UAV was tested on a timber girder bridge structure. The study shows the ability of UAV to detect a variety of damage types on different structural components of the bridge. In an effort to monitor structural health of the infrastructure, Luoa, et al. (2018) developed a video image processing technique to apply vision sensors to structural displacements measurement.

Based on the above mentioned research work, it is found that diversity existed in the big visual data collection and analysis regarding to the requirement from various applications in AEC domain; therefore, it is worth to investigate the big picture of how to apply big visual data based on the requirement of applications and provide a guideline in the future.

3 METHODOLOGY

3.1 Framework

Figure 1 presents a framework proposed in this research project. Four tiers are categorized in the current research stage.

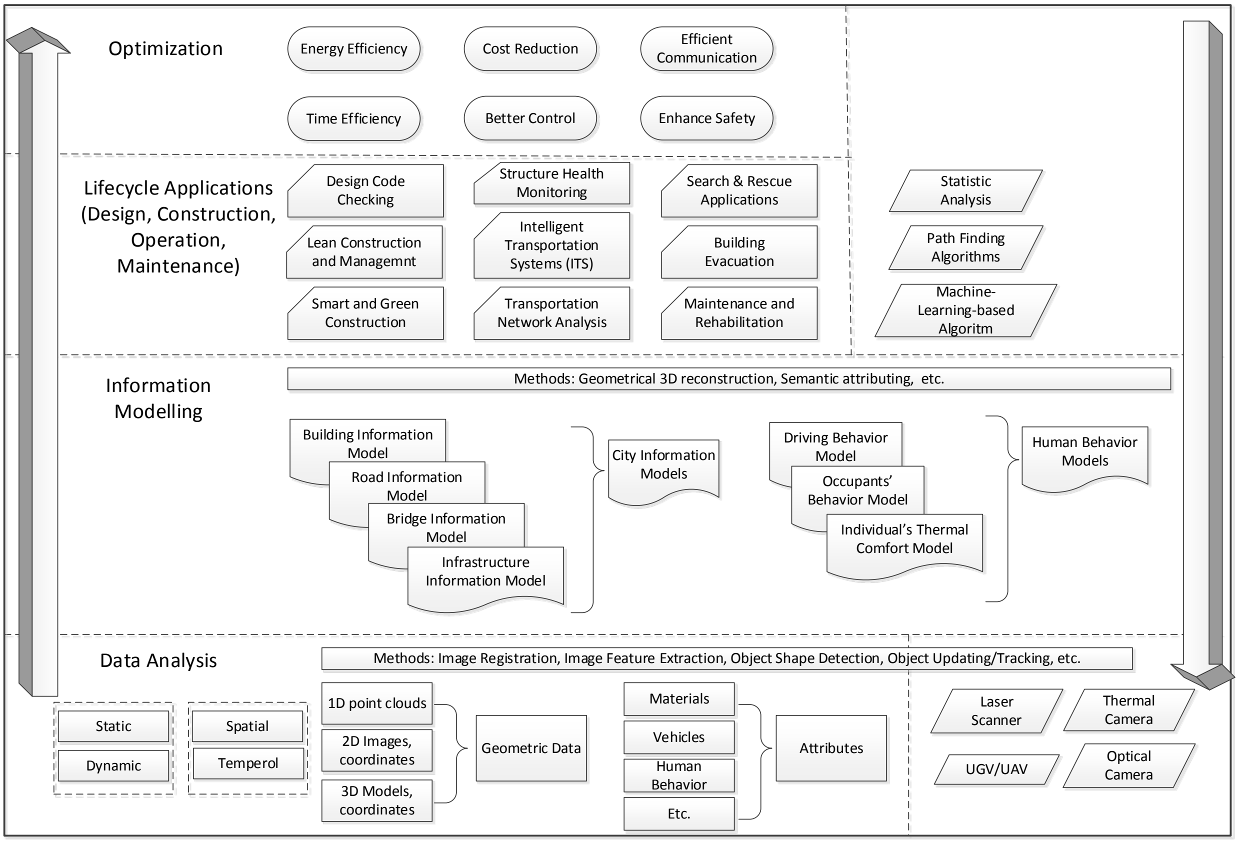

Figure 1 Four Tiers of the Proposed Research Framework

3.2 Data Tier

The fundamental tier is the Data, where raw data, i.e. could points, pictures, videos are collected by using data acquisition technologies, such as optical camera, thermal camera, laser scanner, UAV, etc. During the data acquisition stage, key questions will be investigated and answered. For example, What to collect (Static, Dynamic, Spatial, Temporal, Geometric, Attributes)? How to collect (laser scanner, optical camera, thermal camera, UGV/UAV)? In which form (JPG, EXIF)? For what purpose? How to use? Standard format should be used to save the data in an organized and well-structured mechanism. Upon collection, data will be tested for the following main criteria: 1) Reliability of the collected data (Accuracy and completeness); 2) value to short/long-term applications (Relevance); 3) Speed to Collect, analyze, and reporting at a pace that enables decision making in real time (Han & Golparvar-Fard, 2017). A sequential and automatic framework should be developed to analyze those data, which includes Image Registration, Image Feature Extraction, Object Shape Detection, and Object Updating/Tracking (static/moving object).

3.3 Information Tier

The second tier is the Information Modelling, where data are processed and information are used to build the models of the Built Environment, which should include Geometric, Relation and Attributes. Geometric information can be formed by using 3D reconstruction technologies. Taking buildings as an example, analyze construction performance, an as-built condition needs to be compared to an as-designed condition to capture the dynamic changes on site. One way to achieve this is to align visual data with the as-planned model, which involves manual work — e.g., selection of correspondences between visual data and BIM or placement of surveyed targets (ground control points) for "automated registration." The alignment process is a very important challenge for big visual data because big visual data analytics would not be feasible without a way to scale up this alignment process by automation or even semi-automation. Therefore, this stage will solve the problems associated with 1) alignment of visual data to BIM under various conditions and 2) various aspects of visual data analytics. Structure from motion (SFM) method, which is one of the major surface-based approaches to obtain a 3D structure in the state of motion, will be used to establish the relationship between the different images, so that a 3D model can be constructed accordingly.

Additional to the geometric reconstruction, semantic meanings will be integrated into the information model, where the data collected as attributes in Tier 1 will be processed and associated with corresponding components in the geometric models. As mentioned previously, an as-built geometric model can be reconstructed by using different technologies. However, other attributes are essential to build a meaningful model, which can be understood by both human and computers. Semantic enrichment of building models adds meaningful domain-specific or application-specific information to a digital building model. A set of rules should be developed to encapsulate expert knowledge and to be used to evaluate the topological, spatial, geometric, and other relationships between the model's objects. The output will be a semantic enriched model that incorporates the new information – new objects, property values, and relationships. Semantic enrichment draws on the foundations laid by research of semantic query languages for BIM (Mazairac & Beetz, 2013), semantic rule-checking systems for BIM (Eastman, et al., 2009) (Pauwels, et al., 2011), and BIM model query using spatial and topological relationships (Borrmann & Rank, 2009) (Daum & Borrmann, 2013). However, semantic enrichment has not been widely investigated for other infrastructure. Therefore, an exploratory investigation will be done in this proposed research project.

In addition, human behavior will contribute a big impact onto the performance of the Built Environment during the lifecycle, especially during Operation and Maintenance (O&M) stage. Occupants of buildings, drivers on the highways, users of municipal infrastructures, who will play a vital role in control and manage the man-made facilities in the physical world and present dynamic characteristics in terms of physical spatial-temporal locations. The interaction between human and the built environment can be modelled as well, as can be seen in Figure 1. For example, human behavior can be modelled and analyzed to better understanding or predict in a scientific way. Among which, thermal preference of individuals can be simulated and analyzed to have better control of HVAC to fulfil both energy efficiency and human comfort (Pazhoohesh & Zhang, 2018). Similar research can be done by integrating data from individuals and Artificial Intelligent (IA) algorithms can be applied to this research, which will be discussed mainly in the third tier.

Therefore, together with the City Information Models (CIM), Human Behavior Models will be integrated to form a more information-richer environment, as shown in Figure 1.

3.4 Application Tier

Once the Information Models are ready, Applications can be developed based on real life problems and requirements for the lifecycle of the Built Environment, which is the main content of tier three. Real world cases will be used for presenting various applications that can streamline communication among all project participants, from office to field, and from field to office. Visualization of these methods together into the Integrated Project Model is an on-going research topic. Statistic tools and algorithms can used or tailored to develop solutions for different applications. Through the lifecycle of the building and infrastructure, there are four major groups of applications, which focus on Design, Construction, Operation, and Maintenance. These applications are usually individual applications that deal with specific problems; however, with the developed Built Environment Model (BEM), an integrated consideration can be imaged to envision a larger picture. This is enabled by the interoperability through the fundamental data exchange tool, Industry Foundation Classes (IFC) developed by the BuildingSmart (Anon., n.d.). Interoperability is the ability to exchange data between applications, which can smooth workflow and facilitates their automation. The IFC is a standard data model that supports a full range of data exchanges among heterogeneous applications. Its schema is developed in the EXPRESS modeling language (ISO 10303-11 1997). The IFC data model allows the building geometry and materials property information to be exported from a BIM authoring tool to a standard format such as the IFC compliant STEP (Standard for Exchange of Product Model Data) physical data file (ISO 10303-21). However, Infrastructure-specific IFC data structure has not been fully developed, which will be investigated in depth in this ongoing research project.

3.5 Optimization Tier

The fourth tier will be the Optimization, which shares the algorithms used/developed for the third tier. The main purpose is to guide the Built Environment industry to be more energy-efficient, environmental-friendly, and can provide a comfort and health environment for their users. The optimization level will decide how the Applications will be developed, so as to influence how information is provided and utilized in an organized mechanism. All the above three tiers will have inevitable impact on how to construct the fundamental data tier. Through the bottom-up and top-down bi-directional analysis, much clearer relationships will be built to indicate a roadmap through the lifecycle of the Built Environment under this digital and smart atmosphere. An efficient and technologically advanced industry can be envisioned based on this roadmap and a solid digital foundation.

4 IMPLEMENTATION

4.1 Survey about LiDAR Data Utilization

LiDAR has been used in a variety types of projects for a variety of purposes. It is proved that LiDAR can produce more accurate surveying results in a shorter time period compared to traditional surveying tools. Moreover, it can be potentially used throughout the project lifecycle. The point clouds captured by LiDAR can be processed and used for 3D design model development. As the construction progresses, LiDAR can not only serve as QA/QC tools but also can capture the as-built conditions for future reference or maintenance purposes. In addition, LiDAR data can also be imported into the GIS platform for planning or spatial analyses on a wider scale. A survey was conducted in the US by one of the authors of this paper to study the utilization of LiDAR and its resulting data. Based on the survey results collected from the 17 participants who are working in different state DOTs, LiDAR is mostly used in the planning and design phases (implementation rates 64.7% and 82.4%) while less commonly used in the construction and asset management phases (implementation rates 29.4% and 35.3%). 58.8% of participants used the processed point clouds to develop their initial 3D design models. Other common usages include capturing new as-built features, importing into GIS, conducting QA/QC, documenting historical bridges, developing DTMs, etc. The benefits of adopting LiDAR are obvious, while it is also inevitable to encounter with some challenges of using LiDAR data. Data processing is considered to be the most challenging part (average score 3 out of 5, 5 as extremely challenging), and other common challenges include data storage, computing power, and removing noise in the point clouds (average scores 2.9, 2.5, and 1.9 out of 5, 5 as extremely challenging). More accurate and intelligent tools are needed for extracting the features from the point clouds, so that it can be more efficient to develop the 3D design model from the LiDAR data.

4.2 Point Cloud Data Processing

Point clouds derived using laser scanning and photogrammetric techniques are now a standard type of spatial data for representing geometry and can be used to create 3D geometry models. Although this process remains largely a manual process, some semi-automatic tools were available to accelerate the modelling process with more accuracy and can be found in various software packages such as Realworks, 3D Reshaper and Revit. A common problem with use of point cloud data is that its density may be too high for a given application, leading to higher computational cost in subsequent data processing. In such cases, the density of point clouds is often reduced in the data pre-processing. A uniform reduction over the whole point cloud is a common means of achieving a less dense point cloud. However, this approach does not taken into account the relative importance of individual points and may lead to lose of detail in local complex surfaces (Fan and Atkinson, 2018). To this end, algorithms have been developed to select key points where the local surface is more complex. One approach is based on the local differences (or surface error metrics) between the thinned point cloud and the original one and may involve the evaluation of relative derivations of individual data points from the original point cloud. Another commonly used algorithm is iterative simplification where point pairs in a point cloud are successively collapsed according to a quadric error metric.

The production of models from point clouds is another important data processing step. Depending on the complexity of the surface to be modelled, two types of models may be produced, consisting of geometricprimitives based models and mesh based models. In the former, point clouds are segmented into geometric shapes and fitted by planes, spheres, cylinders etc. In the latter, a mesh model (e.g. triangulated irregular network) can be used to represent a complex surface where a high level of detail is required. The random sample consensus paradigm and the region growing algorithms are frequently used to segment point clouds for identifying geometry objects such as line objects, ground, wall and ceiling. The identification of openings (e.g. windows) is another challenging task and may be achieved using a ray tracing labelling or occlusion labelling algorithm. During segmentation, it is also possible to integrate semantic information to segmented point clouds. Alternatively, the semantic information can be included in the process of geometric modelling of individual elements. Additional information (e.g. intensity data of point clouds or thermal images) may be required to aid the assignment of the semantic information and are possibly useful for the segmentation of some specific objects in point clouds.

4.3 Optical and Thermal Image Processing

Image processing has gained increasing attention in the construction field for progress monitoring, work space analysis and quality assurance. However, a notable downside of image processing is the light condition, particularly for noisy environments such as construction sites. Poor or undesirable ambient light conditions produce low quality images which significantly affect the accuracy of data extracted from related images and lead to a high level of errors. Much research strives to reduce the level of errors in image-based monitoring methods but it still has remained a challenging technique. Therefore, the authors have proposed a method by using thermal image processing, which combines the optical image, thermal image to identify materials and building components on a construction site (Zhang & Huang , 2018) (Zhang & Pazhoohesh , 2017). Infrared cameras can detect the surface temperature of the target objects, so as to add extra information about the presence of the objects with different materials; therefore, the disadvantages of the traditional image-based approach can be mitigated. Infrared cameras have been previously used for adding thermal information of the existing buildings but their utility in reducing the noise of images for monitoring construction activities has never been studied before. The locations and orientation of the thermal camera is obtained onsite to extract corresponding images from the BIM model so as to enable the analysis based on superimposing the optical image, the thermal image and the image from the 3D model after a segmentation process. By combining the results from the cross-matching, objects can be identified with semantic meaning, such as type of objects with associated materials. As a result, an automatic updating of the BIM model with as-built information can be accomplished.

5 SUMMARY

This paper proposed a framework for applying Big Visual Data to the AEC domain by constructing four major tiers so that a guideline can be provided in the future. Some preliminary investigations have been carried out and presented in this paper, which focuses on the fundamental data analysis methods.

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References

Alavi, A. & Gandomi, A., 2017. Big data in civil engineering. *Automation in construction,* Volume 79, pp. 1-2.

Anon., n.d. *BuildingSmart.* [Online] Available at: http://buildingsmart.com/organization/

Bilal , M. et al., 2016. Big Data in the construction industry: A review of present status, opportunities, and future trends. *Advanced Engineering Informatics,* Volume 30, p. 500–521.

Boroujeni, K. A. & Han, K., 2017. Perspective-Based Image-to-BIM Alignment for Automated Visual Data Collection and Construction Performance Monitoring. *Computing in Civil Engineering,* pp. 171-178.

Borrmann, A. & Rank, E., 2009.). Specification and implementation of directional operators in a 3D spatial query language for building information models. *Advanced Engineering Informatics,* 23(1), pp. 32-44.

Bughin, J., Manyika, J. & Woetzel, J., 2017. *Reinventing Construction: A route to higher productivity,* s.l.: Mckinsey Globale Institute .

Daum, S. & Borrmann, A., 2013. *Definition and implementation of temporal operators for a 4D query languages.* Reston, VA, In Proceedings of International Workshop on Computing in Civil Engineering, ASCE.

Dimitrov, A. & Golparvar-Fard, M., 2015. Segmentation of building point cloud models including detailed architectural/structural features and MEP systems. *Automation in Construction,* Volume 51, pp. 32-45.

Eastman, C., Lee, J.-m., Jeong, Y.-s. & Lee, J.-k., 2009. Automatic rule-based checking of building designs. *Automation in Construction,* 18(8), pp. 1011-1033.

Fan, L. & Atkinson, P.M., 2018. A new multi-resolution based method for estimating local surface roughness from point clouds, ISPRS Journal of Photogrammetry and Remote Sensing, 144, Pages 369-378.

Golparvar-Fard, M., Pe˜na-Mora, F. & Savarese, S., 2015. Automated Progress Monitoring Using Unordered Daily Construction Photographs and IFC-Based Building Information Models. *Computing in Civil Engineering.*

Han, K., Cline , D. & Golparvar-Fa, . M., 2015. Formalized knowledge of construction sequencing for visual monitoring of work-in-progress via incomplete point clouds and low-LoD 4D BIMs. *Advanced Engineering Informatics,* Volume 29, pp. 889-901.

Han, K. & Golparvar-Fard, M., 2017. Potential of big visual data and building information modeling for construction performance analytics: An exploratory study. *Automation in Construction,* Volume 73, p. 184–198.

Hamledari, H., McCabe, B., & Davari, S. (2017). Automated computer vision-based detection of components of under-construction indoor partitions. Automation in Construction, 74, 78-94.

Hamledari, H., McCabe, B., Davari, S., & Shahi, A. (2017). Automated Schedule and Progress Updating of IFC-Based 4D BIMs. Computing in civil engineering, 31(4).

Kim, D., Liu , M., Lee, S. & Kamat, V., 2018. Remote proximity monitoring between mobile construction resources using camera-mounted UAVs. Automation in Construction, Volume 99, pp. 168-182.

Liu, C.-W., Wu, T.-H., Tsai, M.-H. & Kang, S.-C., 2017. Image-based semantic construction reconstruction. *Automation in Construction,* Volume 90, pp. 67-78.

Liu, J., Lia, J., Li, W. & Wu, J., 2016. Rethinking big data: A review on the data quality and usage issues. *Journal of Photogrammetry and Remote Sensing,* Volume 115, pp. 134-142.

Luoa, L., Fenga, M. Q. & Wub , Z. Y., 2018. Robust vision sensor for multi-point displacement monitoring of bridges in the field. Engineering Structures, Volume 163, pp. 255-266.

Mazairac, W. & Beetz, J., 2013. BIMQL – An open query language for building information models. *Advanced Engineering Informatics,* 27(4), pp. 444-456.

Omar, H., Mahdjoubi, L. & Kheder, G., 2018. Towards an automated photogrammetry-based approach for monitoring and controlling construction site activities. *Computers in Industry,* pp. 172-182.

Pauwels, P. et al., 2011. A semantic rule checking environment for building performance checking. *Automation in Construction,* 20(5), pp. 506-518.

Pazhoohesh, M. & Zhang, C., 2018. Investigating Occupancy-driven Air Conditioning Control based on Thermal Comfort Level. *Journal of Architectural Engineering (ASCE),* 24(2).

Pučko, Z., Šuman, N. & Rebolj, D., 2018. Automated continuous construction progress monitoring using multiple workplace real time 3D scans. *Advanced Engineering Informatics,* Volume 38, pp. 27- 40.

Seoa, J., Duquea, L. & Wackerb , . J., 2018. Drone-enabled bridge inspection methodology and application. Automation in Construction, Volume 94, pp. 112-126.

Shang, Z. & Shen, Z., 2018. Real-Time 3D Reconstruction on Construction Site Using Visual SLAM and UAV. *Construction Research Congress,* pp. 305-315.

Yang, J., Park, M.-W., A. Vela, P. & Golparvar-Fard, M., 2015. Construction performance monitoring via still images, time-lapse photos, and video streams: Now, tomorrow, and the future. *Advanced Engineering Informatics,* Volume 29, pp. 211-224.

Zhang, B., Zhu, Z., Hammad, A. & Aly, W., 2018. Automatic matching of construction onsite resources under camera views. *Automation in Construction,* Volume 91, pp. 206-215.

Zhang, C. & Huang , H., 2018. *Dynamic As-Built BIM Updating during Construction using Thermal Images.* Auckland, New Zealand, In Proceedings of the 18th International Conference on Construction Applications of Virtual Reality (CONVR).

Zhang, C. & Pazhoohesh , M., 2017. *Construction progress monitoring based on thermal-image analysis.* Taipei, s.n.