AUTOMATED SPATIAL CHANGE ANALYSIS OF BUILDING SYSTEMS USING 3D IMAGERY DATA

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ABSTRACT

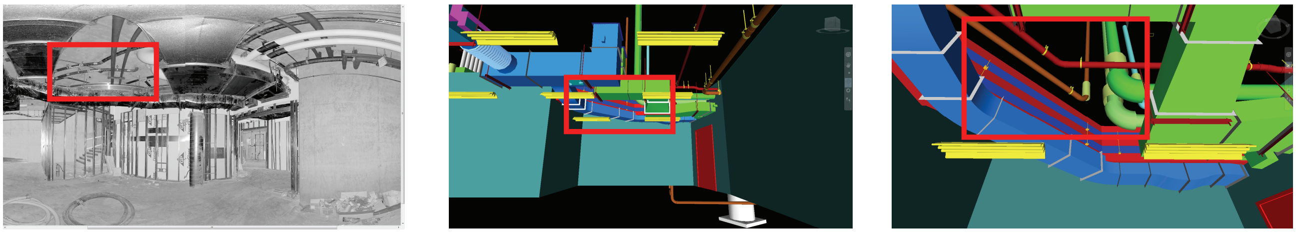
Changes of both designs and construction process usually cause spatial changes in facility design and challenges related to spatial change management between various building systems (e.g., Mechanical, Electrical, and Plumbing) and building components. In practice, design changes can be triggered by the needs of the owner, engineers and experts, resulting in spatial changes of as-designed objects and possibly spatial clashes between them. Spatial deviations also occur between the as-built conditions of building systems components and their as-designed conditions. These deviations are due to changing environments, incomplete design information, and uncertainties in the construction workflows. Spatial clashes caused by changes and deviations need to be addressed through coordination among stakeholders from multiple trades. Such coordination can be tedious, especially when interwoven geometries of building systems components exist. Automated spatial clash detection algorithms are of limited help when the large number of objects interwoven in small spaces, as ambiguities about which points belong to which objects often occur within a space packed with a large number of building systems components.

This paper examines the technical feasibility and scientific challenges of using 3D imaging technology (e.g., laser scanning) to support spatial change analysis of building systems. A review of existing studies indicates that the uses of 3D imaging systems enable civil engineers to acquire detailed as-built geometries frequently in the form of dense 3D point clouds, while posing challenges of handling 3D curvilinear geometries locating close to or even interwoven with each other. Using a case study, this paper shows that currently-adopted neighborhood-searching-based analysis fails in detecting changes of 3D curvilinear objects packed in small spaces, and proposes to model the geometric and topological relationships among 3D curves as the theoretic basis of a robust spatial change analysis approach of building systems.

Keywords: 3D imaging, laser scanning, change detection, building systems, MEP construction, inspection

1. INTRODUCTION

Spatial changes occur frequently during the construction and maintenance of building systems (e.g., Mechanical, Electrical, and Plumbing). As-built conditions of building systems' components deviate from their as-designed conditions (Akinci and Boukamp 2002; Bhatla et al. 2012; Klein et al. 2011; Rojas et al. 2009; Su et al. 2006). Such deviations are caused by design changes, unexpected site conditions, incomplete design information, and uncertainties in the construction operations (Hao and Shen 2008). More changes of building systems occur during the life-cycle of a building (Tang et al. 2010). Figure 1 uses red boxes to highlight an example of design change within the building system of a campus facility. The change shown on this figure is the dislocation of two pipes: the as-designed Building Information Model created in August 2012 only has two smaller pipes in the highlighting box, while the dislocations of the pipes make the constructed building have four pipes in that box. Other types of spatial changes include the shape changes (e.g., variations in diameters of conduits), dislocations, merging and disaggregation of components. Changes of objects in such packed spaces can cause spatial clashes between building components and spatial-temporal conflicts between construction processes (Jongeling et al. 2008). These inconsistencies between building components and construction processes can result in construction delays, costive reworks, safety and quality control issues. Engineers need to track and analyze these changes to achieve balanced project performance among productivity, cost, quality, and safety.



(a) (b) (c)

Figure 1 Spatial changes of the design of a mechanical system: a) 3D imaging data capturing the physical conditions; b) the as-designed Building Information Model (BIM); c) zoom-in view of the as-designed BIM

Understanding the principles underlying various spatial changes and correlations amongst them is critical for proactive spatial change management during the construction and maintenance of MEP systems. In construction, the propagative nature of some spatial changes caused chain reactions of change orders and reworks (S. Han et al. 2012; Park and Pena-Mora 2003). For example, the deviations of conduits from their as-designed geometries cause clashes with other building components (N. Han et al. 2012; Korman et al. 2008; Leite et al. 2010). In packed spaces, resolving clashes can result in further adjustments. Cascading changes escalate construction costs and delays (Hwang et al. 2009; Koch and Firmenich 2011; Love et al. 2010; Rodriguez 2012). Typically, rework costs range from 2% to 12% of contract values (Feng et al. 2008; Josephson and Hammarlund 1999; Love and Li 2000). The total contract value in U.S. was estimated at $798.5 billion for the year of 2011 (U.S. Department of Commerce 2011). Better knowledge about the cascading effects of spatial changes in construction projects can assist engineers identify critical spatial changes that have broad impacts on the project performance. In maintenance, facility managers need to analyze spatial changes of MEP systems for ensuring safe and cost effective life-cycle management (Arayici 2008; Chaput 2008; Huber et al. 2010; Mahmoud and RODZI 2009) and to reduce possibly costly damages to facilities and public utilities (Qiang and Jie 2006). Analyzing the relationships between changes of MEP systems and maintenance activities can guide engineers to identify maintenance strategies that reduce the risks related to cascading effects of these changes.

Within the construction and facility management domain, currently there is not a unified theory about spatial change analysis. Several questions that would help in developing such a theory remain to be answered: *Where and how do spatial changes of MEP systems arise in the field? How can spatial changes be classified based on their nature and impacts? How do spatial changes affect each other and cause cascading effects?* Some studies show the technical feasibility of detecting deviations of physical conditions captured in imagery data from as-designed models for construction progress monitoring (Akinci et al. 2006; Turkan et al. 2010) and urban change analysis (Malpica and Alonso 2010). The change detection methods developed for these studies cannot reliably relate 3D imagery data with corresponding model objects when the scenes are packed with small objects (e.g., mechanical rooms packed with conduits). That results in unreliable answers about which objects have changed and how spatial changes have arisen (*challenge of data-model association*). Previous change management studies investigated the impacts of design errors and changes on performances of construction projects (S. Han et al. 2012; Park and Pena-Mora 2003). These studies assume the reliability of the change data at the project level, while did not explore detailed spatial changes and algorithms for automatically classifying changes based on spatial data. In practice, it is critical to classify and analyze the nature of a change to reduce possible cascading effects of it (*challenge of change classification*). Finally, previous studies conducted limited explorations about automated methods for correlating spatial changes (*challenge of change correlation analysis*). Without automated supports, manually exploring all possible correlations amongst different types of spatial changes is infeasible, as the number of combinations of various spatial changes is exponentially large (Teizer et al. 2007).

This paper synthesizes the potentials and challenges of spatial change analysis of building systems through case studies (section 2) and extensive literature review (section 3). Findings in this synthesis provide insights into the theoretical feasibility of creating a computational framework for automated spatial change analysis of building systems based on relational graphs that model spatial relationships between building components (section 4). Using 3D point clouds collected in a mechanical room within a campus building by a laser scanner, this paper shows the testing results of algorithms that can automatically generate relational graphs of the conduits in this mechanical room, showing the potential of using such relational graphs for automated spatial change analysis of conduits (section 5). The paper concludes with the summaries of findings from the synthesis of research challenges and testing results from the generation of relational graphs based on 3D point clouds, and highlight future research directions within this area (section 6).

2. POTENTIALS OF USING 3D IMAGING TECHNOLOGY FOR SPATIAL CHANGE ANALYSIS OF BUILDING SYSTEMS

2.1 3D Imaging technology for spatial change analysis of building systems

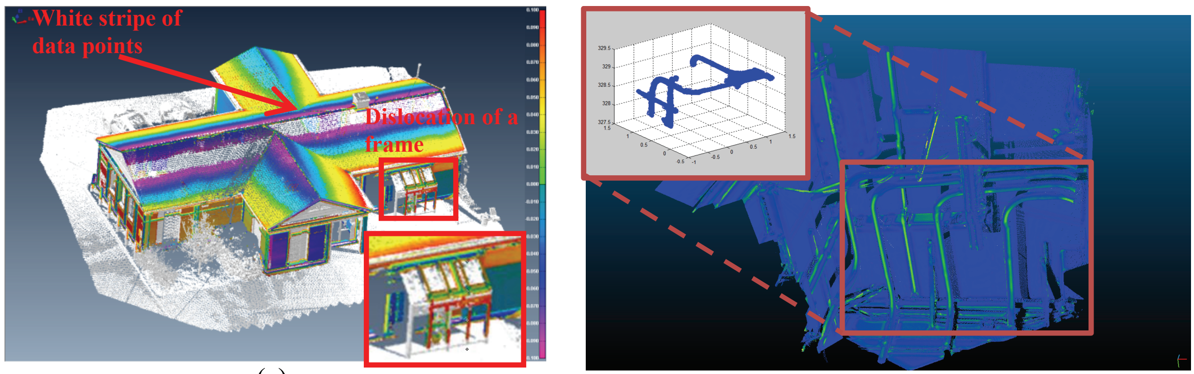
Recent developments in various 3D imaging technologies enable engineers to capture detailed as-is geometric and visual information of constructed facilities and building systems. Three-dimensional (3D) imaging technologies include 3D laser scanning/LiDAR (Budroni and Boehm 2010; Cho et al. 2011; Tang et al. 2010), 3D photogrammetry and videogrammetry (Dai et al. 2012; Fathi and Brilakis 2011; Golparvar-Fard et al. 2009, 2011). A common feature of these technologies is the capabilities of generating 3D data set in the form of “3D point cloud” to capture the 3D geometries of the objects and their environments. The technical differences between them lie in the capabilities of collecting certain visual data in addition to the 3D geometries (e.g., reflectivity and color of the object surface), the time needed for data collection, and the quality of the collected data (e.g., accuracy, density/resolution of 3D data for capturing certain levels of geometric details).

Most 3D imaging systems are able to generate 3D representations of constructed facilities in a few days or even within a day. These representations usually capture objects or building features as small as a few centimeters along all three dimensions (X, Y, and Z). Such detailed 3D data collection and modeling capabilities enable engineers to conduct quantitative analysis of as-built or as-is condition of facilities to understand issues of construction and renovation projects. Some recent studies have started investigating the uses of 3D imaging systems in capturing visual and geometric conditions of building systems (Arayici 2007; Klein et al. 2011; Tang et al. 2010). Building on this existing knowledge, the authors conducted some case studies to understand the technical feasibility and challenges of using 3D imaging technologies for analyzing spatial changes of building systems. The 3D imaging technology explored in these case studies is 3D laser scanning. Two different laser scanners are tested, as detailed in the next subsection.

2.2 Spatial change analysis methods and two case studies

The authors conducted two case studies to explore the feasibility of using 3D imagery data in analyzing the changes of building systems. This research defines “spatial changes” as the deviations of the as-built/as-is conditions of building systems from the as-designed models. In current practice, many projects are using Building Information Modeling technology (BIM) to represent and exchange as-designed models of facilities (Sugihara and Kikata 2012; Tang et al. 2010). Essentially, spatial analysis methods first calculate a “deviation map” between 3D point clouds and as-designed BIM, and then analyze the deviation map to identify spatial changes. State-of-the-art 3D data processing algorithms generate “deviation maps” using neighborhood searching criteria (e.g., Euclidean distance). These methods first associate data points in one source with the nearest surface or points in the other, and then calculate the deviations between associated geometric data along particular directions (e.g., vertical). These algorithms have a “maximum distance” parameter to specify the size of the neighborhood to be searched for matching two geometries. Users can set this parameter based on the expected magnitude of spatial changes in a scene, attempting to maintain reliable matches for most parts of the data while minimizing spurious matches (Akinci et al. 2006; Turkan et al. 2012).

The two case studies focus on analyzing the spatial changes of objects of curvilinear geometries, because most building systems are featured as having a large number of ducts that are of curvilinear geometries. Examples of such curvilinear objects are trusses, ducts, conduits, and frames. The first case study uses a Time-of-Flight (TOF) laser scanner to collect 3D point clouds of the exterior geometries of a campus building in Michigan. The second case study uses an Amplitude Modulated Continuous Wave (AMCW) scanner. Detailed definitions of TOF and AMCW systems are available in (Stone et al. 2004). Figure 2(a) shows a deviation map of a campus building, which visualizes deviations between the as-is point clouds and the as-designed model: red and magenta indicates large deviations (positive and negative values along the normal direction of model surface), while green and blue indicate small deviations. The "maximum distance" parameter was set to 10 cm so that points that are not within 10 cm of the as-designed model are white, the default color of the point cloud. For example, the white stripes on the roof indicate that those points are not associated with the roof, and thus no deviations are calculated for these points.



(a) (b)

Figure 2 Change analysis results of two case studies: a) deviation analysis of a campus building; b) point clouds of the mechanical system of a campus building

Two limitations of the neighborhood-searching change analysis method are highlighted in Figure 2. Using distance as the only measure for data-model association, these methods have difficulties to handle curvilinear geometries of objects that are close to each other reliably, especially when those objects have large dislocations and deformations. In Figure 2(a), a dislocated frame circled on the right is composed of bars having radii smaller than 10 cm. The 10 cm "maximum distance" results in several bars that are not associated with the as-designed model, and the established associations are incorrect: the frame slides along the façade of the building, and the points on some bars are associated with other bars. That is because after sliding, those bars are closer to the data points than the correct correspondences. In Figure 2(b), the authors observed various discrepancies between the as-built data of the mechanical system and its as-designed BIM. These discrepancies include dislocations of ducts, missing or additional ducts. Some ducts also have shape changes, such as elongations and diameter changes. As the geometries of these curvilinear ducts are interwoven, it is challenging to use the neighborhood-search method for reliably associating data points with the corresponding ducts in the BIM. Incorrect data-BIM associations cause erroneous results of change analyses.

Another limitation of current deviation generation and spatial change analysis methods is the lack of formal change classification and correlation analysis approaches. With the deviation maps in Figure 2(b), the goal was to determine the numbers of dislocated, missing, added or deformed ducts. Even though engineers can manually inspect the point clouds together with BIM to identify certain types of changes (e.g., dislocations, missed and added objects, deformations), without having access to an automated change classification approach, it would be necessary to analyze all ducts manually. In addition, changes of the interwoven geometries of ducts will result in spatial clashes and require adjustments to resolve such clashes. The spatial changes of building systems, therefore, have correlations with each other. It would be important for project engineers to understand such correlations so that they can identify more economical adjustments of the ducts. Economical adjustments would be those that will cause fewer propagative changes of the as-designed BIM and thus lower costs for change management. State-of-the-art spatial change analysis methods, such as those clash detection algorithms implemented in Autodesk Navisworks (Autodesk Inc. 2010) and data-model deviation visualization methods implemented in CloudCompare (Daniel Girardeau-Montaut 2011), focus on identifying inconsistencies and changes as individual cases. No methods have been developed for analyzing the correlations between multiple spatial changes of building systems, while manually analyzing large numbers of changes to identify their correlations is tedious.

3. REVIEW OF CHALLENGES AND RELEVANT APPROACHES FOR SPATIAL CHANGE ANALYSIS OF BUILDING SYSTEMS

Results of the two case studies presented above reveal three challenges of using 3D imagery data for spatial change analysis of building systems: 1) *data-model association challenge* that impedes reliable detections of spatial changes of curvilinear objects; 2) *change classification challenge* that impedes efficient and reliable data-driven change classifications; 3) *change correlation analysis challenge* that impedes the discoveries of the relationships between changes for controlling cascading effects of changes. This section will review state-of-the-art methods that are potentially promising for addressing these challenges. Due to the space limits, this paper put more emphasis on discussing the challenges of data-model association, while briefly discussing references and potentially useful methods related to the other two challenges.

Related to the challenge of data-model association, recent studies propose to create relational graphs from 3D point clouds and as-designed models, and then match these two graphs for identifying their correspondences (Zeibak-Shini et al. 2012). A relational graph represents geometric features of building components as nodes. Edges linking two nodes in a graph represent spatial relationships between them. For example, two nodes in a relational graph can represent two ducts; an edge linking these two nodes can represent the "parallel" relationship between them. Compared with the neighborhood searching method, graph-matching methods could result in more robust data-model association, because in many cases spatial changes of objects may not change their spatial relationships. For example, two ducts are parallel with each other. Even after significant dislocations of them occur, they may still be parallel to each other. The "parallel" relationship is relatively robust to dislocations.

Some studies investigated methods that can extract relational graphs based on point clouds or as-designed models. Given 3D point clouds, 3D data segmentation algorithms can group 3D points based on their spatial proximity and similarities in their attributes (e.g., color, normal and curvature of local surface). Feature extraction algorithms can then extract geometric primitives from those clusters of data points, and compute spatial relationships between them (Nüchter et al. 2003; Xiong and Huber 2010). Given an as-designed BIM, the geometric primitives and building component information are already available in the BIM, and it is possible to compute a relational graph as well (Zeibak-Shini et al. 2012). Graph matching methods, such as the one described in (Xiong and Huber 2010), will be able to match two graphs derived from the data and the BIM efficiently to find their correspondences. Two issues challenging such graph-matching processes, however, include: 1) imperfect segmentations of point clouds could cause one duct to be corresponding to multiple clusters of points, or vice versa; 2) spatial relationships between interwoven curves, such as angles and relative locations between them, are changing along these curves as the locations and directions of them change. That brings the challenges of matching two relational graphs while considering possible "n to one" matches between the nodes. So far, no good solutions have been found for such a graph-matching problem. The preliminary results shown in section 5 illustrate this challenge using examples from our case study.

The change classification is a 3D pattern recognition problem. Given the patterns of deviations of 3D points from the as-design model, 3D pattern recognition algorithms will be able to classify them (Tang et al. 2010). The difficulties specific to change classification center around two questions: how to establish a taxonomy of spatial changes that can cover all types of changes of various of 3D shapes, and how to establish the correspondences between certain types of changes in that taxonomy with certain deviation patterns. A classification of spatial deviation patterns is presented in (Anil et al. 2012). That article also discusses how different types of spatial changes can be manually recognized through certain spatial reasoning, and possible ways to formalize spatial reasoning mechanisms for automated spatial change classification.

The correlation analysis of changes is a problem of identifying statistically significant correlations among the locations and other attributes of changes. Spatial analysis methods developed in the domain of Geoscience aim at identifying correlations among observations distributed on both spatial and temporal domains (Anselin et al. 2006). In the case of spatial change analysis, each change would be an observation. Spatial statistical analysis methods, such as "Local Indicators of Spatial Association" (Anselin et al. 2006), can analyze the correlations among observations of spatial changes. The authors are currently conducting explorations along this direction.

4. A RELATIONAL-GRAPH-BASED FRAMEWORK FOR SPATIAL CHANGE ANALYSIS

This paper proposes a computational framework to address the three major challenges identified through above case studies and literature review. Overcoming these three barriers will lead to automated spatial change analysis of building systems for possibly reducing construction coordination costs and delays. Figure 3 shows an overview of this computational framework. This figure shows three stages of analysis corresponding three challenges presented before: data-model association, change classification, and change correlation. The first stage produces a relational graph for the building systems composed of ducts and other mechanical components, and match the graphs derived from point clouds against a graph based on the as-designed model for creating data-model associations. The relationships examined in this paper are "parallel" and "perpendicular;" both are angular relationships between ducts. The second and third steps use the results of data-model association to detect and classify spatial changes within the building systems, and then calculate the correlations among these spatial changes to identify which changes trigger larger numbers of subsequent changes.

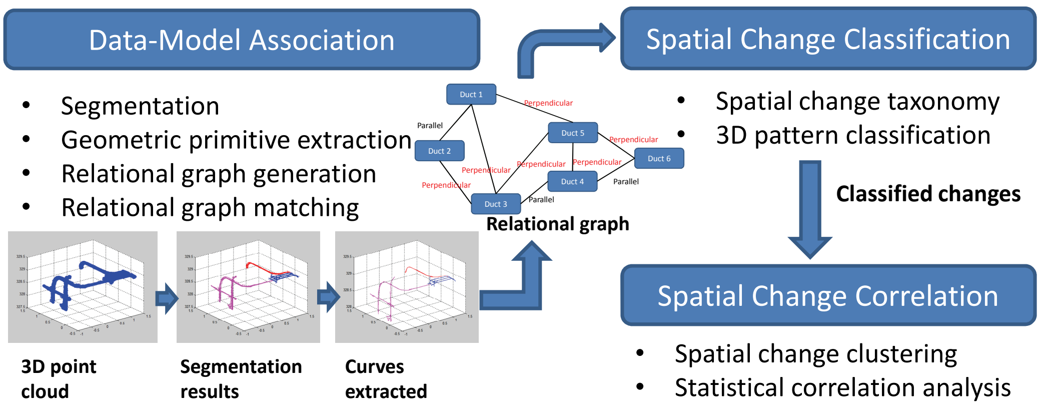


Figure 3 A computational framework for automating the spatial change analysis of building systems (detailed views of the extracted curves and the relational graph are in section 5)

This generic computational framework can have multiple algorithmic implementations. Several algorithms might be able to realize each of the data processing steps shown in Figure 3. This paper focuses on implementing the steps in the stage of "data-model association." This stage contains four steps. Multiple 3D data segmentation algorithms can be used to implement the "segmentation" step, while this research adopts the "Connected Component Labeling" approach (Suzuki et al. 2003). Step "geometric primitive extraction" in this research focuses on extracting curves representing the axes of ducts within building systems. Several algorithms can achieve such curve extractions, while this research adopts the "Laplacian Based Contraction" approach (Cao and Tagliasacchi 2010). The implementations of the steps "relational graph generation" and "graph matching" are currently in progress. At present, the algorithms being explored for "relational graph generation" are the ones presented in (Nguyen et al. 2005) and (Paul and Borrmann 2009). The algorithms examined for implementing the step of "graph matching" are built upon the methods explored in (Xiong and Huber 2010).

5. RESULTS AND DISCUSSIONS

The authors have implemented the steps of "segmentation" and "geometric primitive extraction" that are listed in Figure 3. Some results of executing these algorithms on two data sets collected in a mechanical room within a campus building show the potential and challenges of the proposed computational framework. Figure 4 shows these results. In this figure, the curve extraction results use the different colors for labeling curves identified by the algorithms as belonging to multiple ducts. This figure also shows the relational graphs manually created by the researcher based on the curve extraction results.

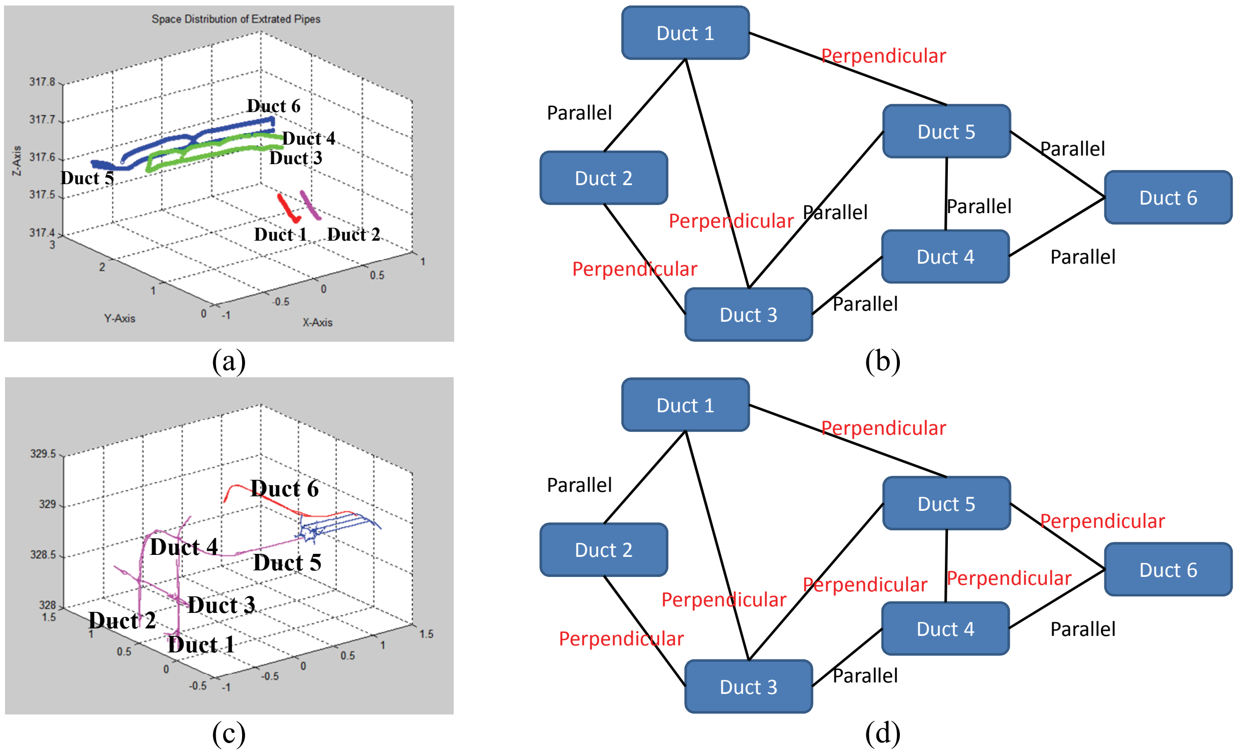


Figure 4 Curve extraction results and relational graphs manually created based on curves: (a) and (b) are results on data shown in the highlighting box of Figure 1; (c) and (d) are partial results on data shown in Figure 2(b)

The results shown in Figure 4 indicate that current implementations of 3D data segmentation and geometric primitive (curve) extraction have some limitations. The major difficulty is that the connected component labeling algorithm will group points belonging to different ducts into one segment. As a result, the curves of multiple curves are grouped into one cluster. For example, ducts 5 and 6 in Figure 4(a) are two ducts, but the algorithm did not split them into two curves. Similar examples are ducts 1, 2, 4 and 5 in Figure 4(c). Such segmentation difficulties cause incorrect relational graphs and thus unreliable data-model graph matching. Future studies will further explore robust methods for reliable 3D segmentation and graph generation to ensure precise data-model association. Given the curve extraction results, the authors manually split these clusters of data points composed of multiple curves, and then use an algorithm that can compute the angular relationship between each pair of ducts to establish relational graphs. Figure 4(b) and (d) show these relational graphs. In future studies, these relational graphs will be matched against graphs generated from as-designed models for data-model association.

6. CONCLUSION AND FUTURE WORK

This paper explores the potentials and challenges of using 3D imagery data in spatial change analysis of building systems composed of interwoven curvilinear objects in packed spaces, such as ducts of mechanical systems. Case studies and literature review indicate the possibilities of automating the spatial change analysis of complex curvilinear geometries of building systems through comparing 3D imagery data against as-designed models. The major challenges include the difficulties of reliably associating data points with corresponding objects in as-designed models (challenge of data-model association), the lack of methods for automatic spatial change classification (challenge of spatial change classification), and the lack of methods for analyzing the correlations between spatial changes (challenge of change correlation analysis). This paper presents a relational-graph-based computational framework and relevant computing techniques that can potentially address these challenges. Testing results in a case study of a mechanical room within a campus building reveal the necessity in exploring reliable 3D data segmentation methods for improving the relational-graph based algorithm for data-model association. Future studies will further explore this relational-graph-based computational framework for achieving automated analysis of building systems to reduce construction costs and delays, while improving the quality. It would also be possible to integrate spatial ontologies and relevant reasoning mechanisms, such as the ontological modeling research presented in (Osman and El-Diraby 2010), into such relational graphs for supporting the graph based data-object association and change analysis.

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