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Application of As-built Data in Building Retrofit Decision Making Process

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Abstract

With the growing needs of improving building sustainability, an increasing number of existing buildings need renovation to meet the expectation of the stakeholders. In the pre-design phase, it is very critical to have the best decision made to satisfy both the project budget and the performance standard. For a new buildings, a whole building energy simulation analysis is very helpful for this decision making process because it can provide the stakeholders the evaluation results of all alternative solutions. However, for existing buildings, the as-built data required for the building energy modeling process is not always available, and its manual collection process is time-consuming and error prone. This paper first reviews the state-of-the-art methods of automated data collection, and then introduces the automatic as-built BIM model creation process through a case study. This study also successfully demonstrated the interoperability between the created as-built model and a typical energy simulation tool. At last, a discussion is made about the limitations and challenges of the current state of practice to enlighten the future direction.

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Keywords: BIM; laser scan; as-built; building retrofit; energy simulation

1. Introduction

Improving Energy efficiency has been a popular subject for the whole world since the energy crisis in the late 1970's [1]. Buildings account for 16 percent of world energy consumption [2], with a higher share in developed

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economies (nearly 42 percent of total energy use in the United States) [3]. While roughly two percent of commercial floors pace are newly constructed each year, and a comparable amount renovated, the majority of opportunities to improve efficiency over the next several decades will be in existing building stock. Thus existing buildings represent the greatest opportunity to improve building energy efficiency and reduce environmental impacts. However, a large number of decision makers lack sufficient information or tools for measuring their building's energy performance, and they are faced with a dizzying array of expensive products and services for energy efficiency retrofit (e.g., as-built 3D modeling services, modeling software, energy simulation software, energy audit services, etc.) with long, uncertain payback periods. The energy retrofit processes could be improved greatly if more reliable information was made available.

The design, construction, and operations of a successful energy retrofit begin with the owner's initial dedication to the project. Building owners and companies must utilize a clear decision process to analyze and justify energy conservation investments. The decision process contains important steps for gathering and analyzing information.

The disconnection between existing high performance building products and the willingness of decision makers to choose those products is likely due to the complexity of both the marketplace and building systems, as well as the lack of adequate feedback loops between decision makers and the outcomes associated with the different stages of the building lifecycle. To fill these remaining gaps, this paper introduces a framework and decision support system to assist decision makers on existing building energy retrofits.

The following sections will first present a background of this study, and then a framework of retrofit decision support system will be illustrated. Following that, the system processing procedure will be presented with a case study on one residential house.

2. Decision Support Systems

For existing buildings, several decision support systems have been designed by researchers. Rosenfeld and Shohet [4] designed a decision support model for semi-automated selection of renovation alternatives. A preliminary survey was revealed to evaluate the condition of the existing buildings, and then different recommendations were made based on the evaluation result. Recently, a new decision support system was proposed to find the most optimized solution in terms of the trade-off between improved quality and investing cost for existing buildings renovation [5]. The solution of this system was determined by a hybrid approach combining A* and genetic algorithms. Although different decision support systems were designed, no one can provide decision makers the information about which part of the building should be renovate based on the results of energy analysis.

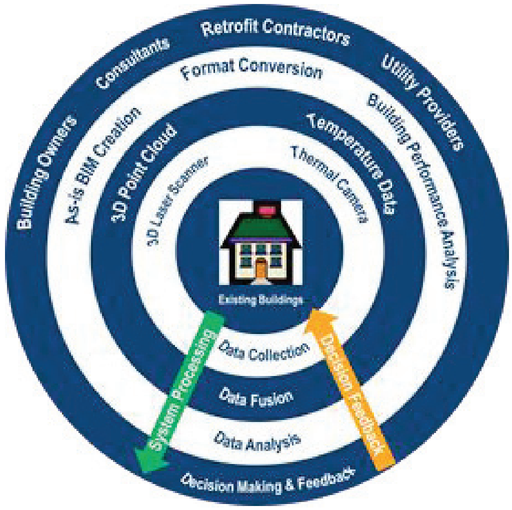

Fig. 1. Framework of the proposed retrofit decision support system.

BIM has been widely applied in architecture, engineering, and construction (AEC) industry, and it can be analyzed in energy analysis software to conduct building energy simulation. However, BIM is not available for most of the current existing buildings. Even though some existing buildings may have BIM, it could not represent the current building conditions since the buildings keep being renovated. The preparation for new BIM is usually labor-intensive, costly and slow. In addition, it is inevitable that different modelers could create different models even though modeling the same building using the same software [6]. Nowadays, this problem can be easily solved using the valuable laser scanning technology due to its ability to acquire building spatial data in three dimensions with high fidelity and low processing time. The output of the laser scanning is an as-is point cloud which is composed of millions of individual points in which each point has its 3D relative coordinate information. Studies have been made on how to create as-is

BIM based on point cloud. However it still needs labor-intensive manual processes to create a BIM out of point clouds.

3. Overview of The Proposed Method

Although much work has been done on the processing of point cloud data for progress in construction and safety monitoring [7], performance visualization [8], and bridge management [9, 10], not much work has been done to facilitate simulation of building performance. Further, as regards practicability, the current point clouds processing technologies are still in the very early stages.

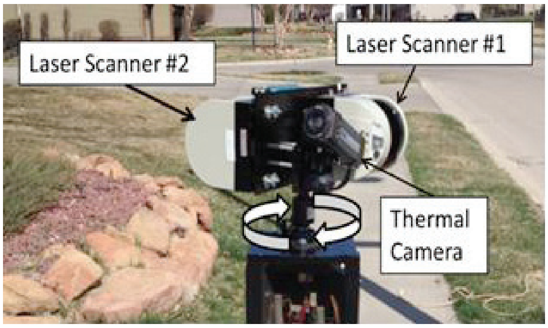

Fig. 2. Robotic Hybrid Data Collection System.

The overall framework of the proposed retrofit decision support system is shown in Fig. 1. First, a hybrid data collection system (Fig. 2) developed in this research simultaneously collects point clouds and temperature data from the envelope of existing buildings [11]. Then thermal resistance value is estimated according to the collected temperature data and the user input. Temperature data and the estimated thermal resistance value are automatically fused with corresponding points during the data collection process. After registering all individual thermal point clouds, a building envelope recognition algorithm is applied to automatically create an as-is 3D geometric model. The as-is model can be imported into energy analysis software through being saved as an industry standard file format. Finally, the feasibility of the proposed method is validated through testing on a residential house.

3.1. Thermal Point Cloud Collection

A robotic hybrid thermal modeling approach was identified to directly fuse the temperature values, other than RGB values, with corresponding point cloud data to create a high-resolution 3D thermal model that overcomes the low-resolution characteristics of an IR camera. To generate complete thermal information about the building envelope, the missing points on glazing areas need to be virtually created.

The test on a Zero Net Energy Testing Home (ZNETH) was conducted. Multiple thermal and laser scans were made to cover the whole building (ZNETH) envelope. The captured thermal data were automatically registered and stored to point clouds on the building surface. After all the point clouds with thermal data were registered, they were rendered by different colors according to the normalized temperature value that was calculated by projecting lowest-highest temperature to 0-1. Here, 0 stands for blue, 1 stands for red. A simple mouse click on any point in the point clouds from the GUI shows x-y-z coordinates and temperature value. For example, a hot point selected in Fig. 3 shows 39.566°C.

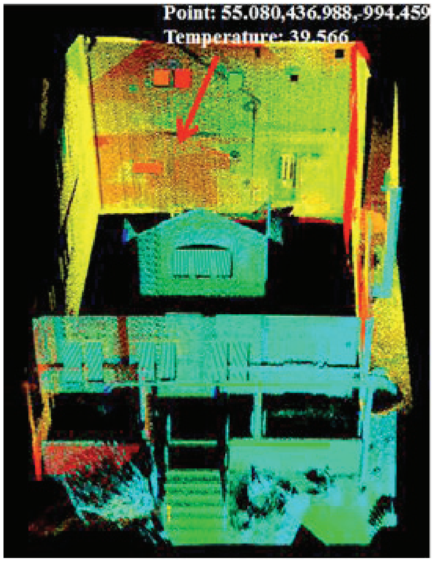

Fig. 3. 3D thermal point cloud rendered by different colors based on normalized temperature values

3.2. Geometry Model Extraction

The collected point cloud data contain the x, y, z coordinates of each point. The proposed method comprises four main steps: first, the collected raw data is pre-processed by removing noise data and downsizing the data. On the completion of data pre-processing, the region growing plane segmentation algorithm is applied to divide the raw data into segments of point cloud which are located at the same plane. Then, a boundary detection algorithm is introduced to recognize boundary points in each segment of point cloud. Further, all the detected boundary points are categorized into their own building component category and building geometry is successfully extracted.

The same residential house (ZNETH) mentioned in last section was used as a test subject. The collected raw data (Fig. 4(a)) containing 1,061,637 points were first processed by the data downsizing algorithm. By utilizing data downsizing algorithm, the data size was decreased to 541,003 points which is about half size of the raw data. The decreased data size can significantly reduce the processing time in the following processes. Then, the downsized point cloud data were segmented into a set of plane clusters (Fig. 4(b)). For each segmented point cloud cluster, the inner and outer boundary points were extracted by a boundary and edge points detection algorithm.

The output of the boundary points detection algorithm was a set of outer and inner boundary surfaces. Then, the rule-based building envelope component classification algorithm followed to categorize each boundary surface into its corresponding category. Fig. 4(c) shows the results of the proposed method. There were total 2 door components, 39 window components, 4 roof components, 1 underground wall component, 1 raised floor component, and 10 exterior wall components being recognized as individual object from the set of boundary surfaces (Fig. 4(e)).

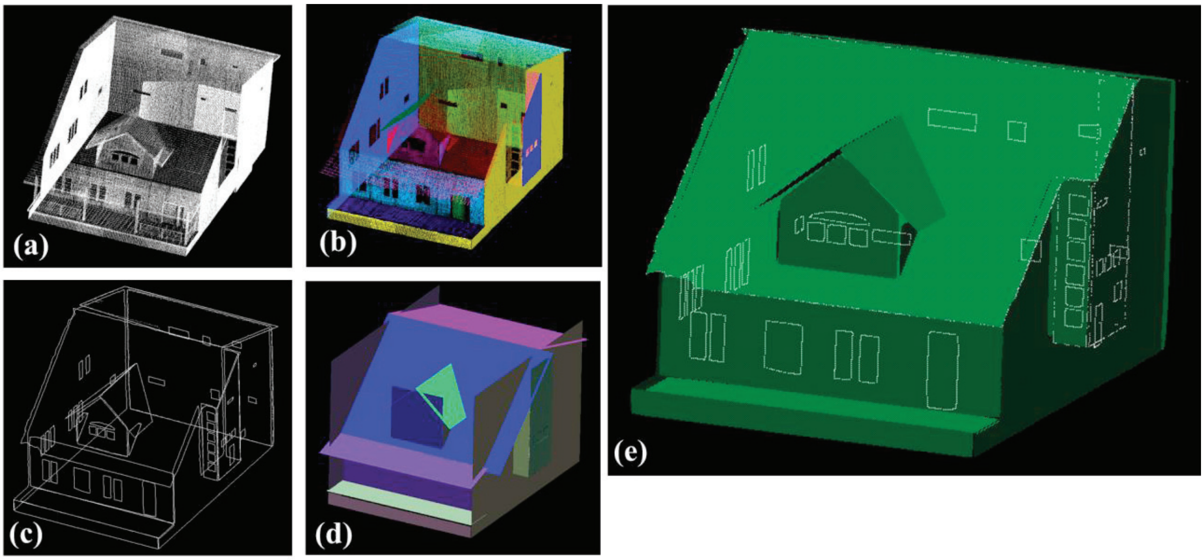

Fig. 4. Extracted semantic model from the thermal point cloud (a) Raw data; (b) Segmented data; (c) Extracted boundary points; (d) Geometry size fitting; (e) Component categorizing.

3.3. Envelope Thermal Resistance Estimation

In this research, the temperature data is collected to estimate the thermal resistance value which is also fused with the corresponding point in the point cloud data. Since it is not the scope of this study, the method of estimating the thermal resistance value is briefly demonstrated in the following, and the details of the method and validation test results can be found in the previous research effort [12].

Based on the advanced heat transfer principle, the envelope thermal resistance value can be acquired from Equation 1, where R_w is thermal resistance of the wall, R_o is exterior wall surface resistance, dominated by the external convection capability, $T_{s,i}$ is inside surface temperature, $T_{s,o}$ is outside surface temperature, T_o is outside air temperature, h_o is heat transfer coefficient and can be calculated according to Equation 2 and Table 1. In Equation 2, V_z is Local wind speed, and D, E, F is material roughness coefficients. The inside surface temperature T_i may be approximately replaced by inside air temperature for simplified calculation. $T_{s,o}$ can be measured from the IR camera, and the other input parameters can be obtained from other sensors equipped in the system and the user input.

$$R_w = \frac{T_{s,i} - T_{s,o}}{T_{s,i} - T_o} \bullet R_o = \frac{T_{s,i} - T_{s,o}}{T_{s,i} - T_o} \bullet \frac{1}{h_o} \quad (1)$$

$$h_o = D + E \bullet V_z + F \bullet V_z^2 \quad (2)$$

Table 1: Roughness coefficients

Roughness Index	D	E	F	Example Material
1 (Very Rough)	11.58	5.894	0	Stucco
2 (Rough)	12.49	4.065	0.028	Brick
3 (Smooth)	10.22	3.1	0	Smooth Plaster
4 (Very Smooth)	8.23	3.33	-0.036	Glass

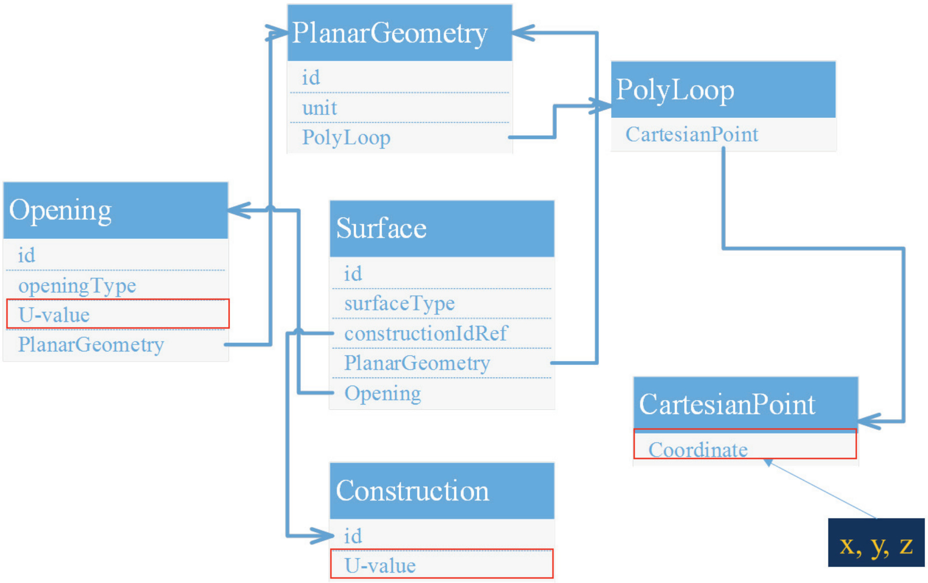

Fig. 5: The gbXML schema of the elements used in data exchange.

3.4. Data Conversion

The output of the building component classification algorithm was a set of boundary points of the envelope components. For each individual component, all its boundary points were saved in a text file in which the first line of data was its surface ID, and followed by its surface type and thermal resistance value on the same line. The thermal resistance value of each envelope component was estimated by averaging the thermal resistance value of all the points located on this component surface. Starting from the second line, there were three columns of data on each line, and they represented one point's x, y, and z coordinates. To be useful for energy simulation, the file has to be converted to another file format that can be imported. In this research, the Green Building XML (gbXML) open schema was chosen to help facilitate the transfer of the data to engineering analysis tools. Fig.5 is a structure chart of element "Surface" in gbXML schema (Version 5.0.1). This element was used to interpret the extracted components. Each surface requires a unique ID, surface type, and geometry. Surface type includes interior wall, exterior wall, roof, ceiling, and etc. In this paper, exterior wall and roof were assigned to corresponding surface. PlannarGeometry specifies the location of the surface, and lists all vertexes of the surface to define a loop. Attribute "Opening" is added if there is any opening in the surface. In addition to the building geometry data, the estimated thermal resistance value is also attached in the gbXML file. In each segmented point cloud cluster, every point has its corresponding estimated thermal resistance value. The average thermal resistance value of all the points in one cluster was used to represent the thermal resistance value of the corresponding recognized building envelope components. In gbXML schema, the “Construction” element is a combination of layers, such as a wall or a roof. The calculated thermal resistance value can be attached to its attribute “U-value”. Then, the id of the “Construction” element needs to be bonded with corresponding surface. The extracted as-is data were first saved as text files, as shown in Fig. 6, and then were converted into gbXML file according to the corresponding gbXML schema.

4. Feasibility Validation

In previous sections, this study discussed about how to collect 3D thermal point cloud data, and how to automatically extract building envelope geometry from the point cloud data. The output from the previous sections was an auto-generated gbXML file. The motivation of this research was to reduce labor-intensive and time-consuming traditional processes to measure as-is conditions of building envelops including geometry and thermal value, thus saving significant time and efforts for the data and information preparation which are required for building energy analyses and simulation. The intent of this section was to validate the feasibility of using the auto-generated gbXML file as an input in the energy simulation tools. Fig. 7 shows the preliminary result that the auto-generated gbXML file of the tested ZNETH was successfully imported into a building energy simulation tool (Autodesk Ecotect Analysis 2011 was tested for validation in this study.).

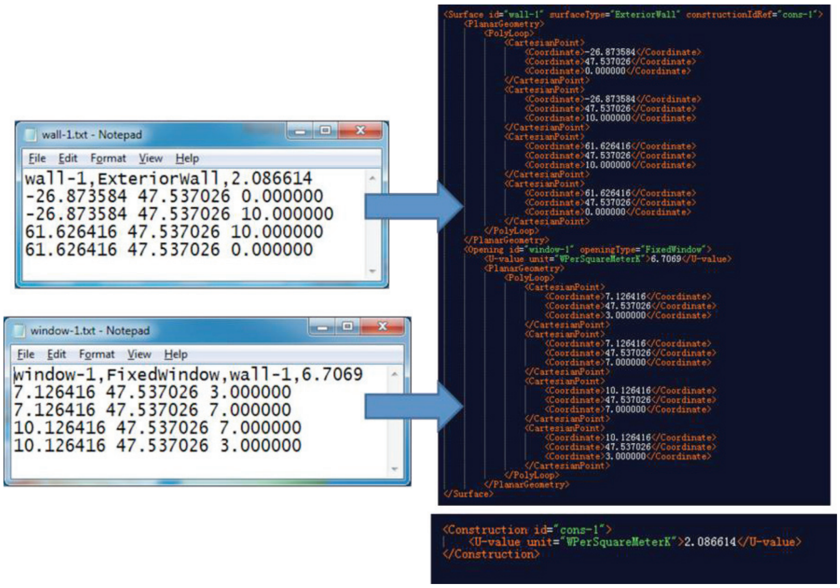

Fig. 6: Data exchange from text data (left) to gbXML data (right).

5. Conclusion and Future Work

This research proposed and demonstrated a framework for automatic gbXML building model generation from the thermal point clouds collected from the custom developed hybrid data collection system. In the proposed method, the thermal resistance value were estimated based on the collected temperature data of the building envelope and other sensor data. A semantic building geometry model was extracted from the raw data. Together with the geometry and thermal data, a gbXML model was created based on the gbXML schema, and this generated gbXML model can be successfully imported into the building energy simulation tool. The preliminary case study shows the feasibility of the proposed method and the potential of automating the thermal model preparation process. The future work will extend this research to develop a cloud-based service system that can utilize this generated gbXML model for sustainable decision making.

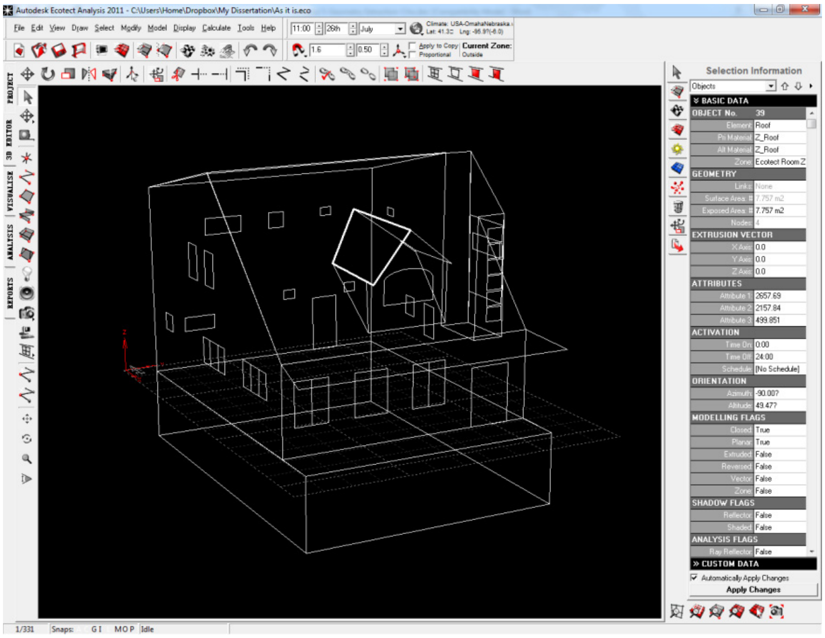

Fig. 7: Auto-generated gbXML file imported into Autodesk Ecotect

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