Integrated Building Assessment to Enable Retrofit Design, Fabrication and Verification: A Drone-based Approach

SyracuseCoE Faculty Fellow Program Report

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Technical description of project

1. Overview

Buildings account for approximately 40% of annual greenhouse gas emissions in the United States. In New York State, approximately 80% of residential and commercial buildings were constructed before the emerging energy codes in the 1970s [1]. Therefore, there is a significant need for affordable and scalable building retrofit solutions with low embodied emissions to meet the targets in the NYS Climate Leadership and Community Protection Act of 2019. A building energy audit is the initial step to quantify a building's energy performance and reveal its energy-saving potential. However, performing a high-level energy audit requires detailed field analysis and is often time-consuming and expensive. Therefore, there is a need for digital solutions to make different parts of the building assessment process affordable, efficient, and scalable. The overarching goal of the project was to develop a drone-based technique that automates building envelope inspection procedures and collects data for developing semantic-rich models for retrofit design and verification.

2. Data Requirements for Building Energy Retrofit Design and Fabrication

Several organizations in NYS (e.g., NYSERDA) are adopting Integrated Physical Needs Assessment (IPNA) reports that merge building ASHRAE energy audits with conventional ASTM physical needs assessments to reduce duplication of effort and reach economies of scale for building inspections [2]. The New York City Building Department has also outlined standard practices for energy audits and retro-commissioning of base building systems [3]. Additional standards, such as ASTM E2841-19 and ASTM E2270-14, address unsafe conditions related to facades, while historic structures necessitate an extra layer of review under IPMC. The NYC façade inspection program also defined the process and requirement for periodic inspection of exterior walls and appurtenances of buildings [4]. Despite these established standards, they primarily cater to regular maintenance rather than retrofitting design. The building assessment services (e.g., IPNA) mainly collect information related to existing buildings' performance. We did not address those data categories related to the building performance as they were already defined by the literature in a standard way. While the standard practices for building inspections often include creating a building energy model baseline, they rarely include creating the digital model of the building (3D point cloud or BIM).

The term "as-built BIMs" refers to models reflecting a facility in its constructed conditions [5]. However, for most existing buildings, BIMs are unavailable or outdated due to ongoing renovations [6]. Although creating accurate as-built BIMs is challenging, it is essential for designing and fabricating building energy retrofit solutions. Although historically, BIMs were introduced in the 70's, gaps in technology and knowledge prevented the construction industry from equipping facilities with as-built BIMs, until recently that some projects and studies proposed approaches with this regard. Recent advancements in the 3D reconstruction field, particularly in Computer Vision, have bridged technological gaps by offering tools for generating 3D models. Architectural, structural, mechanical, plumbing and control systems, electrical power and lighting, fire protection, special equipment are different types and examples of what a building owner should expect to receive as part of the as-built modeling package [7]. Various data requirements for assets, as outlined in [7], should adhere to recommended principles, including standardized naming conventions (building number, year, discipline designations), essential asset properties (the properties of manufacturer, description, model and serial number), and accompanying documentation (appropriate spec sheets, installation manuals and O&M manuals). All assets should be placed dimensionally accurate; assets not directly bound within a room will be captured via the nearest room's area boundary.

BIM serves as a facilitator for reliable prefabrication, aiding in early issue detection, material tracking, and computer-aided manufacturing. Table 1 shows the constraints for retrofits [8]. The study conducted interviews and identified BIM-related interruptions as; inconsistencies in BIM and existing site conditions (23%); rework on prefabricated assembly (23%); clash on site (28%); waiting on communication (13%); lack of technology use (8%); and out of sequence work (5%).

Table 1. Constraints for retrofits [8].

Constraints
Information (lack and uncertainty of existing data)
Time (acute pressure for time to market of product)
Space (space congestion, access and work sequencing)
Environment (working with hazardous or toxic materials, noise & vibration)
Maintaining optimum production levels
Demolition & disposal of hazardous materials
Maintenance of Environmental/Health/Safety (EHS) requirements

Access for production workers
Removal or protection of existing equipment
Reuse of existing equipment
Experimental studies of uncertainties in design
Late changes in retrofit design

In this context, determining model requirements is crucial, considering the trade-off between cost and data density. The level of detail (LOD), building elements, and non-geometric attributes emerge as vital categories. It is essential to identify the LOD of the model because higher modeling accuracy improves the reliability of the as-built BIM for the use in retrofit design and fabrication application. However, the higher the level of detail, the higher is the cost [9]. Scan data quality attributes, such as accuracy, space resolution, coverage, and others (e.g., location, angular resolution, etc.), play a crucial role. The as-built model creation that is based on the points in the building category to identify building elements for BIM with LOD300 (good for building design development that can be used in the construction stage). LOD measures the reliability and completeness of building elements geometry and information from LOD100 (pre design) to LOD500 (as-built). From the BIM point of view, LOD300 might be appropriate for creating building models for retrofit design purposes. It should be noted that the acceptable accuracy is important for two separate purposes of retrofitting design and fabrication, in addition to energy assessment. It should be noted that for retrofitting, the level of accuracy might be application dependent, and the mentioned level might be the minimum requirement. However, for the energy model development, additional simplifications might be needed because this level may represent the geometry and features (e.g., overhangs) that might not be needed for the geometry input and considering thermal zoning set up. Additionally, Level of Accuracy (LOA) is another metric that enables professionals in the Architectural, Engineering, Construction, Owner (AECO) industry to specify and articulate with clarity, the accuracy and means by which to represent and document existing conditions (specifically for the accuracy of scan data) [10]. In particular, the LOA30 and 40 (with two standard deviations of 5-15 mm and 1-5 mm, respectively) are preferred for use in retrofit design and fabrication. Balancing these considerations is essential to optimize the reliability of the as-built BIM for retrofit design and fabrication applications.

3. Drone-based Data Collection

The potential use of drone-based nondestructive inspection techniques has been explored both to assess structural building conditions [11] and identify envelope defects in the literature [12], [13], and [14]. The team designed and conducted experiments to test the effectiveness of using a drone equipped with visual, and thermal infrared cameras to collect data from the building exterior and achieve the building assessment needs. Building inspections were conducted with a DJI Mavic 2 Enterprise Dual drone for testing the workflow. Federal Aviation Administration (FAA) has established Small UAS Rule Part 107 for operating small UASs in the United States, which has lowered the barrier for commercial drone applications. The FAA has developed a UAS Data Exchange, Low Altitude Authorization and Notification Capability (LAANC), to facilitate sharing airspace data between government and private industry. LAANC allows drone pilots to receive a near real-time authorization for operations under 400 feet in controlled airspace around airports [15]. After receiving the required authorizations from the FAA, a site visit was needed to design the flight path with minimum obstacles. Various software applications (e.g., B4UFLY, Aloft, Pix4Dcapture, and DJI Pilot) were used to pre-plan the flight control. Two sites were considered for data collection, including Baker Laboratory at SUNY ESF and Building Envelope Systems Test (BEST) lab facility at Syracuse University.

The vertical flight path was selected and designed for inspecting the East facade of the Baker Laboratory (four-story building) on the SUNY ESF campus located in Syracuse, New York. Figure 1 shows the rectangular path with dimensions. A distance of 6.5 meters away from the finishing of the building envelope with one meter step for capturing images were considered in the flight path design step, resulting in a 90% image overlap that was implemented for gathering data. Therefore, the threshold range of 70 - 80% overlap suggested for rectangular flight path, considering auditing and visualizing building energy use, provided in [12], was respected. A spring evening time with a partly cloudy sky and stable temperatures without precipitation were used for conducting the experiment.

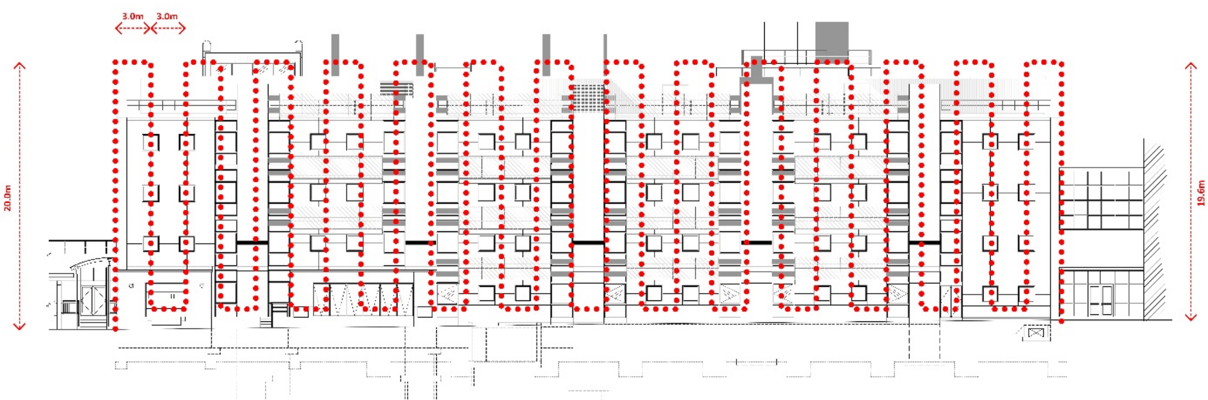

Figure 1. Vertical flight path design for the Baker Lab.

For the BEST lab case, elliptical and rectangular flight paths were designed. In addition to the drone experiment, the team conducted laser scanning and collected baseline data to compare the level of accuracy of the drone-based approach. Figure 2 demonstrates an elliptical flight path designed for creating a 3D point cloud of the building, in addition to the actual camera path over the tie points. A rectangular flight path was designed and conducted as well, which is more useful for an automated vision-based envelope inspection [16]. Pix4Dcapture (with circular flight capability) was used to control the drone during the elliptical flight. Three different altitude scenarios of 18.3, 24.4, and 30.5 m were considered and called Scenarios 1, 2, and 3, respectively. The top view design of the flight plan for collecting data was taken with a 10° angle between images. The experiment was conducted in mid-August, during evening time with a semi-cloudy sky and stable temperatures without precipitation. Air temperature of 23.3°C and relative humidity of 41% were recorded during the experiment.

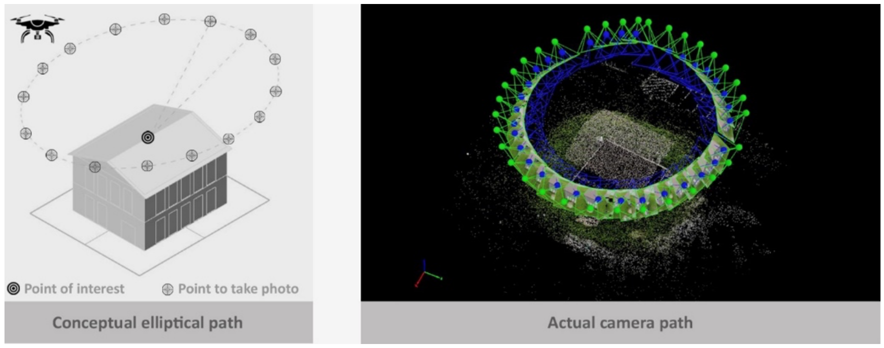

Figure 2. Elliptical flight path design (left) and actual camera path (right) for the BEST lab experiment.

4. Implementation of Semantic Segmentation and Reconstruction Techniques

For the purpose of 3D point cloud creation, the Pix4Dmapper was used with the collection of BEST lab input images. The pixels from images were extracted and a point cloud model was created. This step was done by triangulating individual pixels from multiple geo-located images. Initial processing was needed to create tie points, which is the preliminary step for creating point clouds and mesh reconstruction. Figure 3 shows the result of point clouds and classification for three different altitude scenarios. By implementing the deep learning algorithm, the data has been classified into ground, road surface, vegetation, building, and human-made objects. Then, the building class has been separated and exported to Autodesk ReCap, which can then be translated into a building energy model [17].

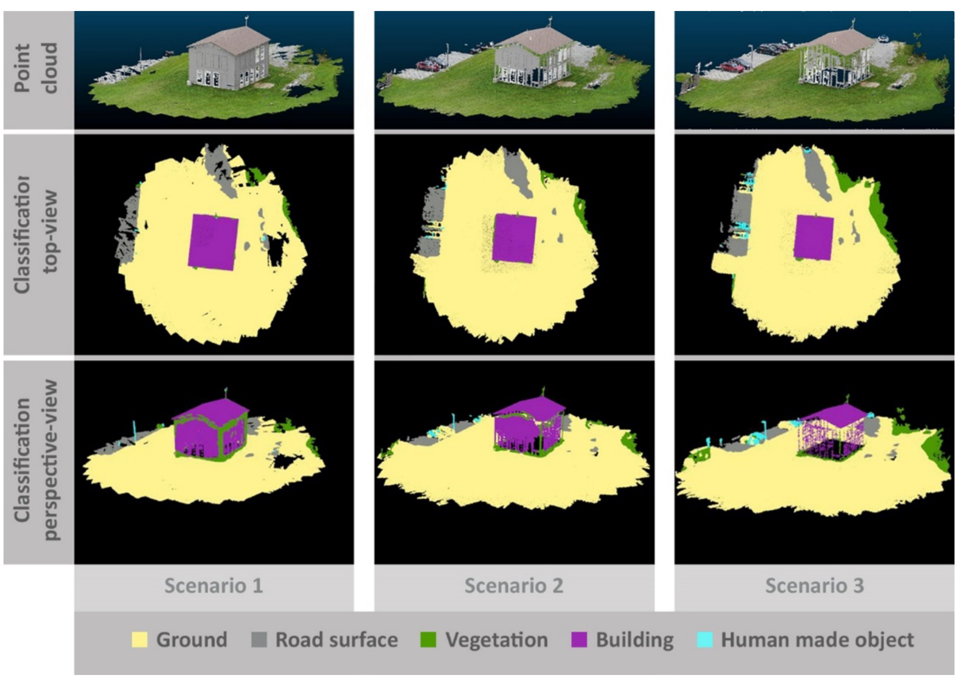

Figure 3. Point clouds and classification results for three different scenarios.

As expected, according to point clouds, Scenario 1 with lower altitude showed a more precise model. The observed trend is that by increasing the altitude from 18.3 m to 30.5 m, the quality of the point cloud at the corners of the building is reduced. This can be characterized by the angle of taking pictures from the camera to points of interest. From the perspective view, false-positive points have been labeled as vegetation along the vertical corner edges and behind the roof overhang. CloudCompare software was used to compare generated point clouds from drone-based to laser scanning approach. Figure 4 shows the results of Cloud-to-Cloud (C2C) absolute difference maps to two methods. The standard deviation was also reduced from 0.054 to 0.028 mm, after tuning and comparison.

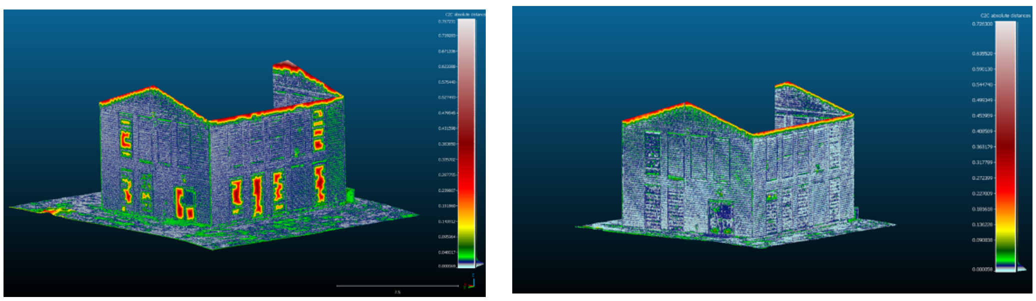

Figure 4. C2C absolute difference map of two approaches before (left) and after (right) parameter tuning.

Various 2D and 3D semantic segmentation approaches were reviewed. Semantic information based on 2D images has made a lot of progress recently, but because of its limitation in occlusion, computational complexity and other data aspects, its performance for 3D data is not satisfactory. In general, working with 2D images and 3D point clouds are very different. Images are collected as data sets using a camera device, however, point clouds are collected using laser scans, photogrammetry, SLAM, structured lighting, videogrammetry, and drone-based techniques [18]. The 3D problem is a much harder problem than 2D processing. It is difficult to perform convolution operations on irregular and disordered 3D point clouds directly [19] because of the nature of the data itself. 3D algorithms can be divided into four categories including attribute-based methods, model-based methods, machine learning and graph-based methods [18]. It should be noted that considering the context of this problem, models based on deep learning have superior performance and reach a higher benchmark in comparison with the traditional algorithms. Zhang et al. [19] has divided these approaches based on deep learning into direct and indirect point cloud segmentation method. Figure 5 shows this overview of this categorization [19].

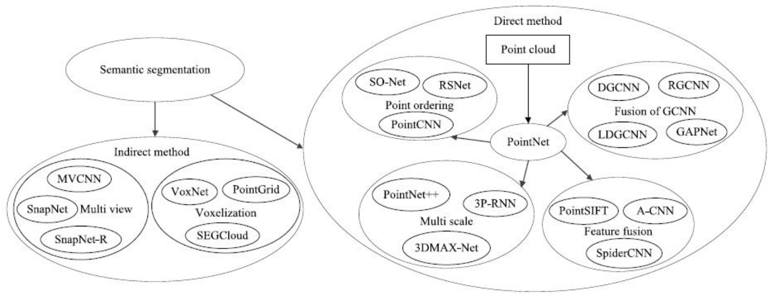

Figure 5. Visual representation of 3D semantic segmentation methods [19].

Indirect methods convert the point clouds into the regular structure based on multi-views and voxel grids [19]. In the multi-view based methods, 3D data is transformed into 2D views and then algorithms are applied to extract features for processing. PointNet is a novel architecture that directly consumes point clouds, which well respects the permutation invariance of points in the input (Figure 6) [20]. Multi-layer perceptron (MLP) is employed to extract features for each point separately, and then maximum pooling is used to aggregate the information of all points [19]. Furthermore, this framework adds the transformation network, which constructs the transformation matrix to spatially align the input point clouds and features. There are other algorithms that have been developed based on PointNet. Although, one limitation of this network is failing to consider relationship between points and their neighborhood, and it may not be appropriate for processing of large scenes due to loss of information, it was used here based on its performance for the context of this problem.

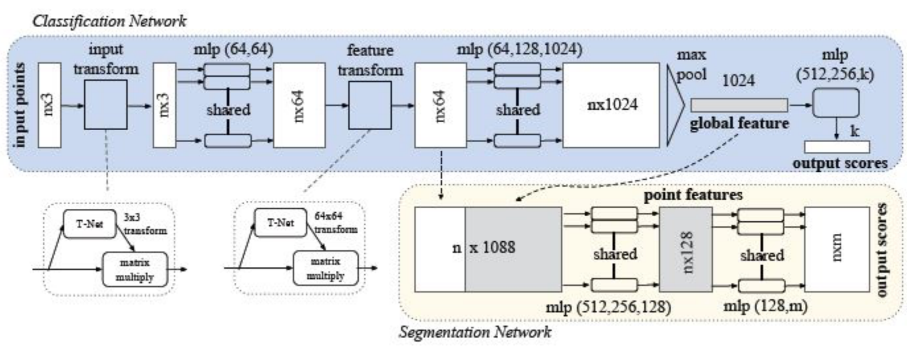

Figure 6. The framework of PointNet [20].

The Stanford 3D Indoor Scene Data Set (S3DIS) for training a 3D semantic segmentation model was used [21]. The data set contains point clouds of indoor spaces from several buildings. The elements used for the reconstruction. Figure 7 shows an example of a scene for training with colors denoting different classes.

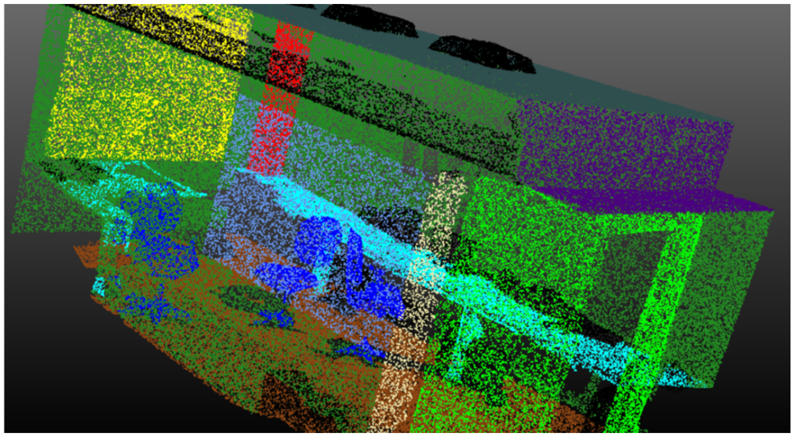

Figure 7. Example of segmented elements.

For the development of the dataset for semantic segmentation of building elements, the annotation task was carried out using the software LabelMe, which is an open-source graphical image annotation tool. The images contained various elements that needed to be annotated. The different elements were annotated with specific colors for ease of identification, and the JSON files were then converted into a PNG image format. This conversion was performed to enable a more visually intuitive representation of the annotations, which is particularly helpful for understanding the semantic information within the image. Figure 8 and 9 show the steps of the annotation task for images from Baker and Best lab collected dataset.

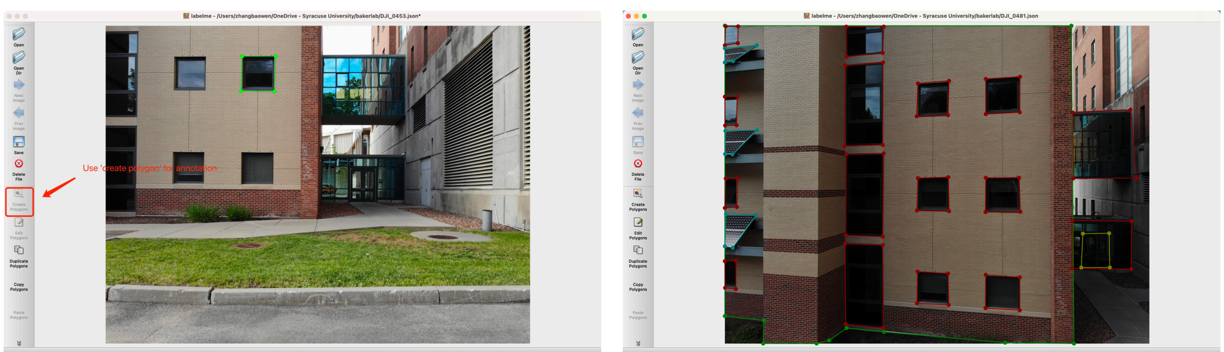

Figure 8. LabelMe annotation example.

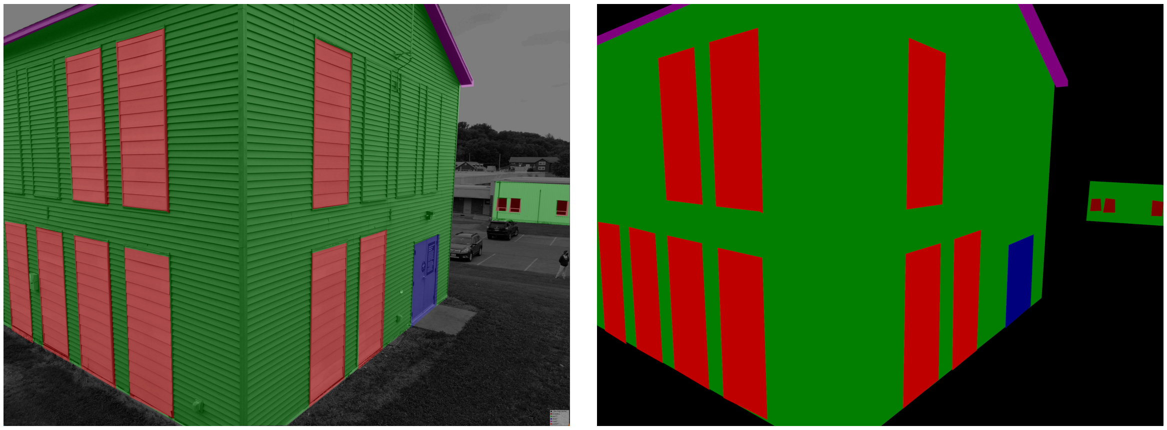

Figure 9. Completed segmented PNG example.

Figure 10 shows the developed workflow for thermal anomaly detection based on sematic segmentation.

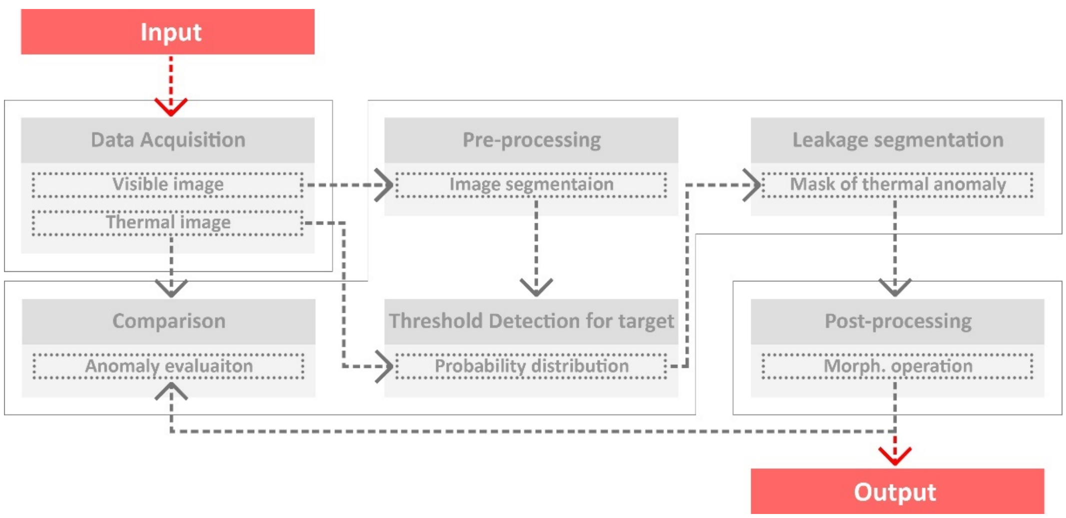

Figure 10. The workflow for thermal anomaly detection.

Thermal anomalies were characterized by sharp temperature changes in thermal images [22]. Following the automatic anomaly threshold detection approach provided in [23], and improved by [24], the probability distribution of the target class (domain) was estimated [25]. To prevent misclassification due to anomalies in excessively small areas, a certain percentage is excluded. The two largest local maxima are searched. The value with the smallest probability between the two is assigned as the threshold (see Figure 11). It should be noted that distribution with one global maximum was assumed to follow unimodal distribution. After detecting the threshold for the target, the actual leakage areas were segmented. Then, as a post-processing phase, morphological operations were applied to smooth the mask. This process is iterative and may be repeated for various classes of target envelope components that are considered in the detection phase.

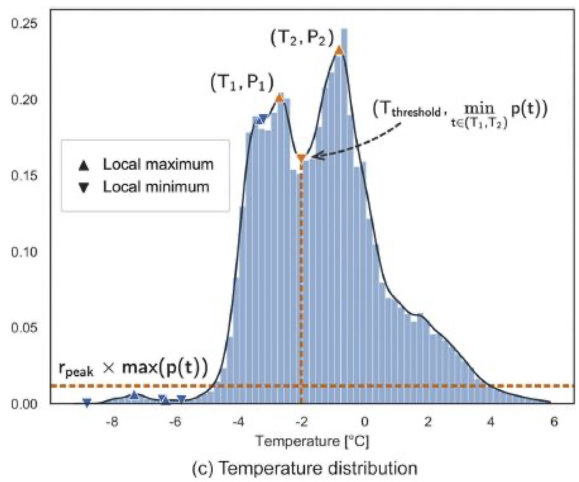

Figure 11. Probability distribution and anomaly threshold detection approach [25].

Figure 12 shows U-Net model architecture for semantic segmentation that can be trained to identify walls, roofs, windows, and doors from building images [26].

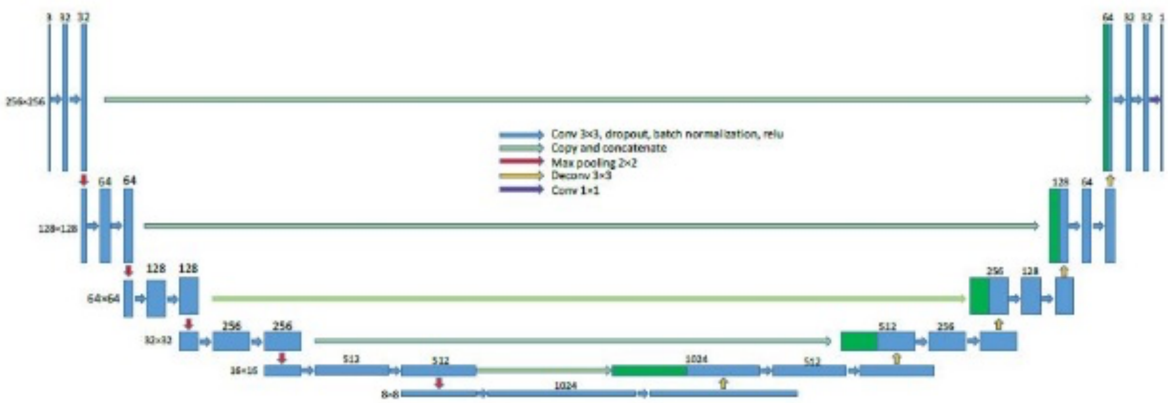

Figure 12. An instance of U-Net model architecture provided in [26].

Figures 13 shows an instance of an image from the eTRIMS dataset, true label class, and predicted label class. The segments are used to separate the target domains to apply the anomaly detection procedure, and the performance of the training can be improved as well.

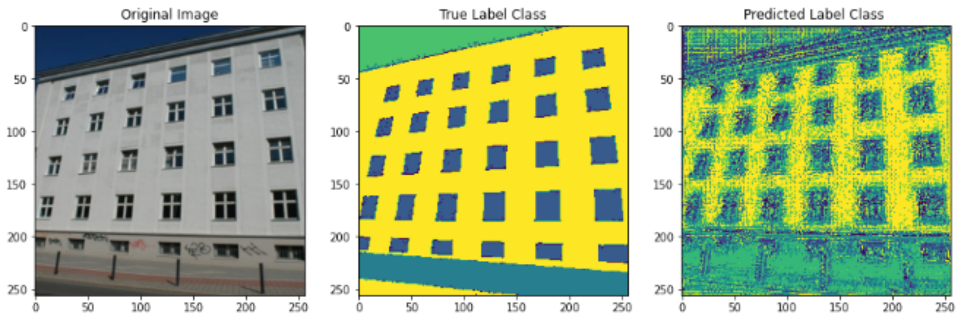

Figure 13. An instance of an image with predicted label class.

Then, the procedure for detecting envelope components was tested. A case of material degradation and deterioration is provided in Figure 14. In this case, after detecting the thermal threshold from the probability distribution of the whole image, leakage was segmented, and the mask of the thermal anomaly was created. However, after separating the target domains of wall and window, separate probability distributions were characterized. In this wall domain thermal scenario, an anomaly was represented from the right end of the inspected façade. Figure 14, an example that is provided here, illustrates a portion of the two top floors of the building in addition to sky presence. It shows that the performance was clearly improved. The cases of deterioration for the wall and losses around the window were the results of the detection procedure provided by this example. The precision and recall were 87% and 82%.

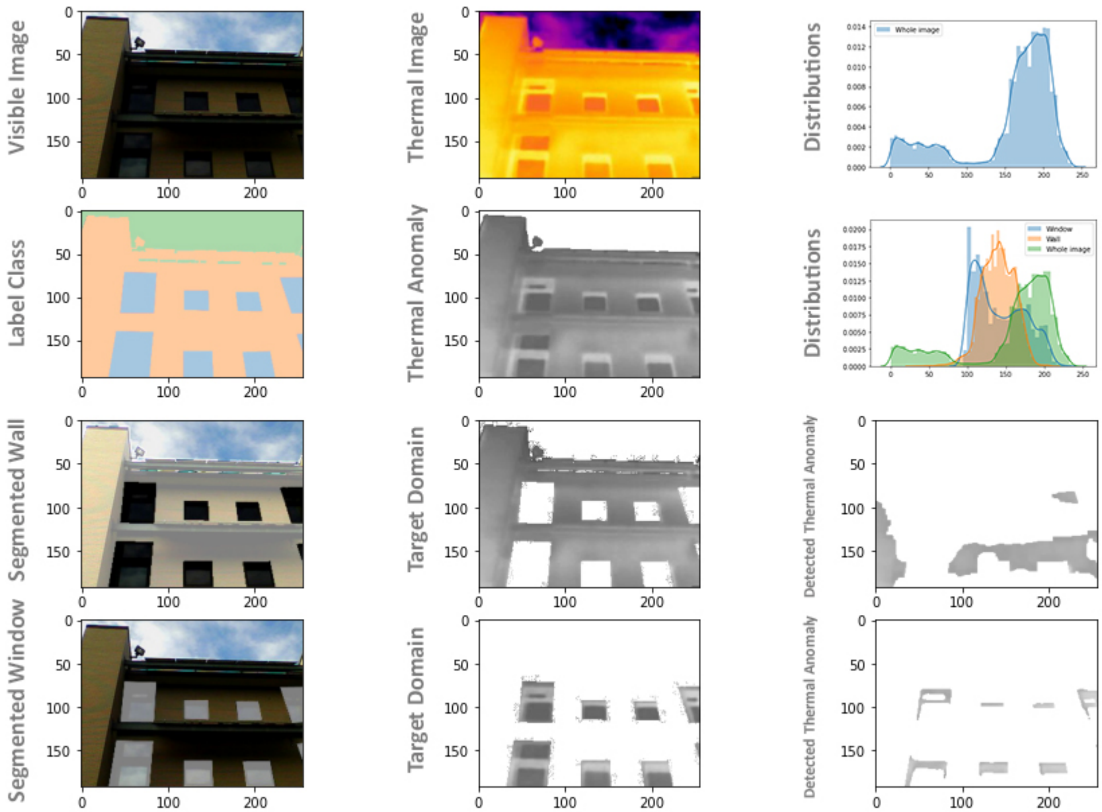

Figure 14. Visible and thermal images and the anomaly detected for the whole image, in addition to targeted segmented walls and windows with the final results of detected thermal anomaly for those domains.

Another approach of anomaly detection using the Canny edge detector was also published in [16]. Figure 15 provides examples of three samples of this analysis. Sample 1 illustrates the case of the addition of a beam to a wall representing a possible geometrical thermal bridge that was captured through the IR image and presented on top of the visible image. A case of material degradation and deterioration, combined with air leakage, was possibly detected in Sample 2. In this thermal scenario, which is represented from the right end of the inspected facade, this anomaly might be caused by the high exposure of building material to weather scenarios compared to the intermediate areas' materials, where the protection was provided by large ducts located in the right and left side of the portion of envelope. Sample 3 shows the possible air leakage around the small fenestration was successfully detected.

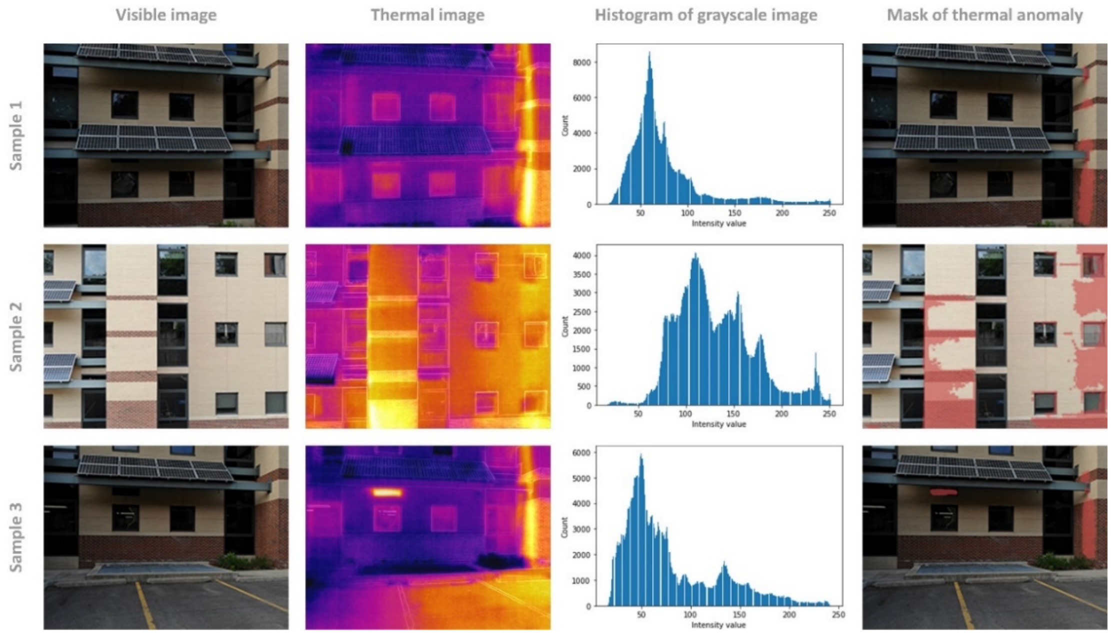

Figure 15. Sample of visible and thermal images taken with the drone thermography and the final detected thermal anomalies.

5. Development of Workflows for BIM Data Exchange

BIM has been widely used in the Architecture, Engineering, and Construction (AEC) industries for various purposes. An existing building may not have a 3D or BIM model. In the most traditional way, paper-based 2D drawings or digital documents are data sources for generating a BIM model. Although BIM is an important player in this sector, it barely reflects reality such as shading, true color, and actual building components' dimension. A semantically rich parametric model can be defined as a model that contains two types of data, geometric data and nongeometric data [27]. Therefore, BIM methods for converting point clouds into semantically rich building models by detecting and classifying objects in the point clouds, have been developed by researchers [28]. Some of the challenges associated with the conventional process are the loss of reality and details during the geometric modeling process, and not being feasible during construction because of time and labor considerations for the classification and modeling process. To address these challenges, semantic segmentation can be used for automatic object segmenting and information labeling [29]. The previous section discussed the segmentation. Lack of reliable data structures for managing the semantic information and exchange from classification to information representation (in terms of data interoperability) are still challenges in this context. Nongeometric data are commonly manually appended using BIM software (or in another format). Another challenge is BIM software cannot process data not covered in IFC format. IFC was developed by buildingSMART over the last several years. It is the most widely used set of standards for exchanging information about a building among diverse IFC-compliant BIM applications. The key points when using an IFC file are the file format, IFC version, model view definitions (MVD), and file structure [30]. Apart from IFC, there are other spatial data standards including City Geography Markup Language (CityGML), and Indoor Geography Markup Language (IndoorGML)) that have been developed in order to make interoperability of spatial data for specific applications easier. All that being said, IFC is the format that is used in AEC, and it has an object-oriented structure. The physical representation of IFC is expressed in the standard for the exchange of product (STEP) or Extensible Markup Language (XML) format. Geometric data is taken primarily from point cloud processing. Typically, nongeometric data are appended manually in current practice. However, nongeometric data can be also extracted from other sources. BIM data interaction with other formats creates challenges. There are various data schema including web ontology language (OWL) and ontology for IFC (ifcOWL), but they are designed to extract data from existing building models. Another data schema is ifcJSON. The main point of developing these schemas is to use existing information about buildings and convert it into OWL ontologies [31]. The collected data first were aggregated into RDF data as the unified data format (standard format for data interchange). RDF can describe the semantics embedded in the data and combines multiple data sources. Next, it was classified into IFC-compliant or Non-IFC Compliant data (remains in the form of RDF data associated with the model).

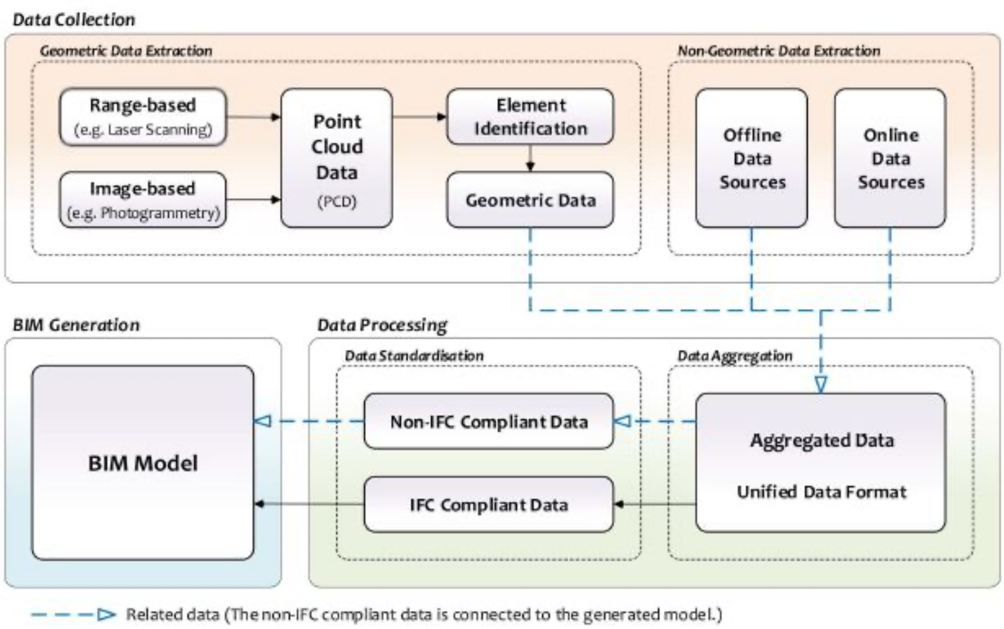

Figure 16. BIM generation framework [31].

There are also semi-automated software packages for this purpose, such as Kubit PointSense and EdgeWise. For the latter, manual selection of object category for structural elements, not being able to achieve semantic labeling of cylindrical objects and only being compatible with .c3db format are some of limitations. For the former, as an example, manual selection of object types is a challenge. Other challenges of geometric modeling in this process are including the loss of reality and details, time, labor and cost considerations for the classification and modeling process [32]. Feature selection can also help with the extraction of features for explaining planes. Dimensionality reduction and unsupervised learning were used to explore the discriminative ability of the final feature set as well as emergent class groupings. The final stage was also supervised learning. Figure 17 shows an example of DBSCAN, RANSAC implementation, in another research, to extract points associated with planar objects from the original point clouds [33].

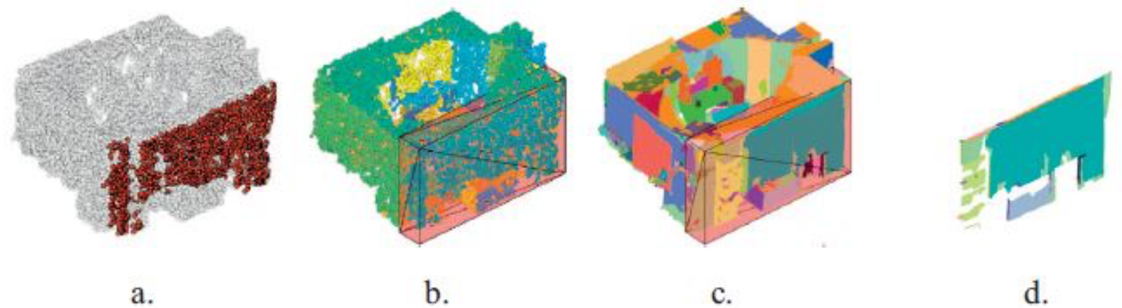

Figure 17. Extraction of planar objects from the original point cloud. (a) planar object in the downsampled point cloud as identified by 6D DBSCAN, (b) planar object in downsampled point cloud defined region of interest, (c) RANSAC is applied to extract planar object from original point cloud, but search is constrained to region of interest, (d) extracted planar object with label "wall" [33].

Recent algorithms improved the performance of scan-to-BIM but there are other challenges. A large amount of learning data is required when there are more categorization items. The connection between segmentation and BIM still needs additional details for automation and improving the process. For outdoor scene and façade segmentation, training data set creation, considering building objects, shapes, materials, it is critical that an international effort be established. Furthermore, there is a need for algorithm development for adding objects with various shapes to the library. This task is needed to utilize the existing BIM data standards and resources to generate inputs for building energy simulation.

The developed workflow is shown in Figure 18. The general steps include (1) the flight path design and collecting data for 3D point cloud creation; and (2) creating the building model and developing energy simulation [17].

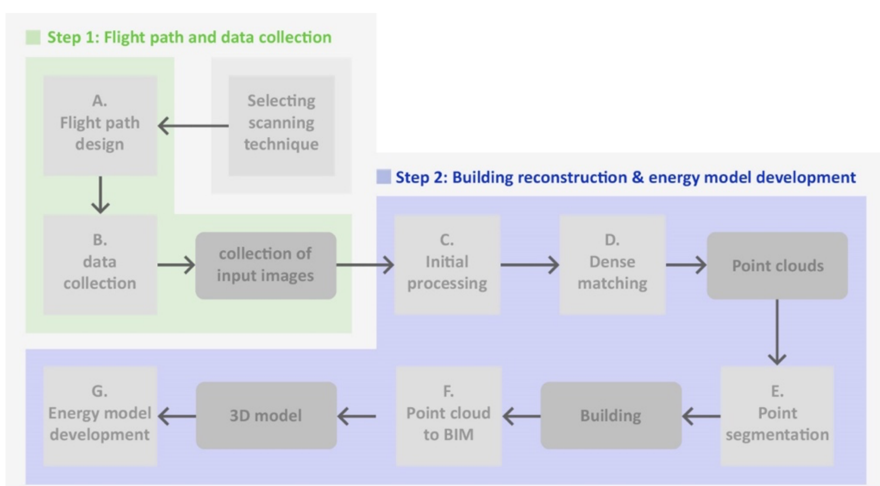

Figure 18. Workflow for the building reconstruction and energy model development.

After segmentation, the constructed elements were taken into Autodesk ReCap software to create a whole 3D model. Then, the constructed model was transformed into the Rhinoceros 3D environment. This model was used to provide inputs for building energy modeling. Thermal simulation engines (e.g., EnergyPlus) require a 3D model to be a closed volume. Therefore, a 3D model that does not represent a closed volume can not be used for this purpose. The workflow was verified by running a successful energy simulation, using EnergyPlus, which is handled via Honeybee in the Grasshopper interface. The default construction set of Honeybee was assigned to the building model, and other simulation parameters were reported in [17], according to residential use. Furthermore, the hourly annual weather data was selected for Syracuse from the EnergyPlus Weather (EPW) repository. Figure 19 shows the energy intensity results of the heating and cooling for the simulated case.

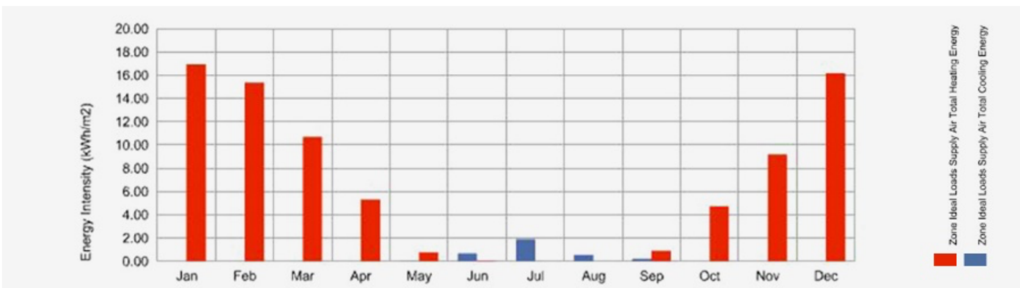

Figure 19. Energy simulation results.

The results show that the energy simulation model is debugged. Therefore, a successful simulation was performed using the developed workflow.

6. Research Methods for Building Material Reuse and Recycle Assessment

The data processing and model development for building inspection and retrofit design is time-consuming and requires technical expertise. However, existing assessment techniques fall short in meeting specific data requirements for circular design and offsite fabrication of retrofit solutions. To address this gap, a deconstruction analytics system is essential for providing end-of-life performance assessment from the design stage. In this section, we present a summary of reviewed studies focusing on reconstructed Building Information Modeling (BIM) data with rich semantics to facilitate material inventory assessment, enabling recycling and reuse of existing building materials, thereby reducing embodied emissions. This summary lays the groundwork for identifying gaps and serves as the basis for future research and proposal developments.

Deconstruction, as a building end-of-life scenario, enables the efficient recovery of building components for reuse, recycling, or remanufacturing [34]. Crucial computational tasks in this context include material classification, object classification, and spatial reasoning. The Industry Foundation Classes (IFC) data format is well-suited for handling geometric, material, and other construction-related information. Additionally, exploring data formats such as RGB and RGB-D alongside IFC may be necessary for effective deconstruction analytics. In addition to the IFC data format, it would be possible to customize a data schema representation. For instance, a recent research study proposed a data schema to represent the classified information with an object-based hierarchy structure, with the possibility of its extension to other areas including mechanical, electrical, and plumbing (MEP) engineering [35].

Another study implemented the sequential exploratory mixed method strategy and contributed to the area of effective material recovery through Design for Deconstruction (DfD), especially for diverting waste from landfills [36]. Additionally, to understand how BIM could be employed for DfD and to identify essential functionalities for a BIM-based deconstruction tool, Focus Group Interviews (FGIs) were conducted in [37]. Although previous studies suggested developing data schemas for building deconstruction or material reuse, but a validated and publicly available standard is lacking [38]. One proposed solution is the Disassembly and Deconstruction Analytics System (D-DAS) architecture, comprising a Data Storage Layer, Semantic Layer, Analytics and Functional Model Layer, and Application Layer. This architecture integrates building design information, material specifications, and deconstruction data, sourced from BIM models, into a NoSQL database. Authors proposed a NoSQL database because of the diverse nature and variety of data that will be stored by the storage facility. The semantic layer employs Deconstruction and Disassembly Analytics XML (DDAXML) for data exchange formatting and provisioning [38]. The data provisioning functionality provides the application layer of the architecture with access to databases. The functionalities of D-DAS are developed at the Analytics layer (e.g., Building Whole Life Performance Analytics, etc.). The application layer is a platform that the functionalities of D-DAS are made available to the users and is implemented in two ways. The first implementation is the Plug-in for the existing BIM software (e.g. Revit). The second implementation of D-DAS functionalities is a standalone application that is based on simulation and visualization tools (e.g., 3D Max, Unity, Unreal, Maya, Stingray etc.). In that study, the demolition data contains historic data of deconstructed buildings, that includes information about building properties and corresponding demolition wastes and recoverable materials. However, the actual data collection as an input for the storage layer was not discussed.

For retrofitting existing buildings, data collection methods include laser scans, photogrammetry, Simultaneous Localization and Mapping (SLAM), structured lighting, videogrammetry, and drone-based approaches. Drone-based techniques were explored for material characterization, although the volume of data required may pose challenges [39]. Data augmentation can be considered to address limitations in small-sized datasets, which have been implemented in other field, such as biomedical engineering. As mentioned, a challenge for implementing segmentation algorithms on point clouds is the lack of labelled databases for training (with specific problem consideration). To address this, in addition to using publicly available databases and the efforts for developing datasets by manual annotation, it would be possible to use PointSampling algorithms to generate labelled 3D points from triangular mesh geometry of individual building components from IFC files [40].

Based on the review, a comprehensive framework involves data collection, data preparation, classification and geometric modeling, (primitive shape detection, semantic classification of detected shapes and fitting), and semantic enrichment. Data preparation is important with a data filtering and down sampling. All data preparation and processing can be done in Python environment with the available libraries, in addition to deep learning packages implementation using the Pytorch or TensorFlow. For the purpose of classification and segmentation, an instance of an effective algorithm implementation for material and object classification can be PointNet++ provided in [35] and histogram computation for spatial reasoning. Then, the processed data first are aggregated into Resource Description Framework (RDF) file as the unified data format (standard format for data interchange) both from the point clouds processing and recognition, in additional to external online and offline data source that are needed to be aggregated. Then, it is classified based on the format. A BIM software (e.g., Revit) can be also used to visualize the file. Alternative algorithm implementations, such as DeepLabv3+ and Depth-Aware CNN, can be explored for segmentation purposes. Although Bejgrowicz and Rydgård [39] demonstrated that DeepLabv3+ exhibited superior performance based on the evaluation metric of mean intersection over union [41], for the implementation of a deconstruction project, it may be advantageous to conduct a comprehensive comparison among various algorithms, utilizing a range of evaluation metrics.

In conclusion, we reviewed research methods for building material reuse and recycle assessment, and the methodology should encompass a holistic approach to building material reuse and recycle assessment. The proposed framework, based on the review, aims to bridge the gap in existing assessment techniques and provide a comprehensive solution for effective building deconstruction and material reuse, that can be implemented in future research proposals and projects.

Outcomes

The project outcome includes the workflow with various implemented algorithms, a semantic segmentation dataset, articles, and the report that can be further used for writing proposals. The outcomes will also contribute to developing new knowledge on the data requirements for building assessment required for retrofit design, fabrication, and material reuse. Additionally, the research findings also contribute to updating standards for integrated building assessment and defining data schema requirements for the interoperability of digital models. Furthermore, the implementation of state-of-the-art computer vision and artificial intelligence algorithms helps improve the performance of scan-to-BIM and BIM-to-BEM workflows.

Accomplishments

The poster from this project titled “Automated Building Inspection for Thermal Anomaly Detection and 3D Reconstruction Using a Drone-based Approach” was presented at the Systems and Technologies for Remote Sensing Applications Through Unmanned Aerial Systems (STRATUS) 2022 Conference and won the best poster award. This conference is one of the best conferences in the remote sensing application area. Another accomplishment was the development of the “Exterior Building Envelope Components Dataset for Semantic Segmentation” that contains annotated building images. It is one of the first unique datasets for the building semantic segmentation that will be published and helps implementation of various artificial intelligence algorithms for the built environment.

Benefits

This project advances SyracuseCoE’s research objectives relating to energy efficiency and healthy buildings. The main objective of the building energy retrofit design is to reduce operational energy needed for heating and cooling, and other end uses to minimize the operational emissions of the existing buildings. However, with operational efficiency improvements of facilities and further decarbonization of the electric grid, it is critical to consider the embodied emissions of the retrofit solutions. Therefore, this project contributed to developing a fast and scalable building inspection solution for building assessment while providing additional benefits by collecting data required for the design and fabrication of retrofit solutions and assessing the possibility of material reuse and recycling. It also contributed to economic development in NYS for the NY Retrofit targets and making the overall process more affordable.

Publications

- Mirzabeigi, S., Razkenari, M., & Crovella, P. (2024). Thermal Anomaly Detection of Walls and Windows via a Deep Learning-based Semantic Segmentation. Automation in Construction (Under Preparation).
- Mirzabeigi, S., Zhang, B., & Crovella, P. (2024). Exterior Building Envelope Components Dataset for Semantic Segmentation. Nature Scientific Data (Under Preparation).
- Mirzabeigi, S., Razkenari, M., & Crovella, P. (2024). Automated Thermal Anomaly Detection through Deep Learning-based Semantic Segmentation of Building Envelope Images. ASCE International Conference on Computing in Civil Engineering (i3CE 2024) (Submitted).
- Mirzabeigi, S., Eteghad, P., Razkenari, M., Crovella, P., & Zhang, J. (2022). Drone-based scanning technology for characterizing the geometry and thermal conditions of building enclosure system for fast energy audit and design of retrofitting strategies. 6th Residential Building Design & Construction Conference (RBDCC), 251-260. https://www.researchgate.net/profile/Shayan-Mirzabeigi/publication/360461605
- Mirzabeigi, S., & Razkenari, M. (2022). Automated Vision-Based Building Energy Assessment Using Drone Thermography. Construction Research Congress 2022, 737-746. https://doi.org/doi:10.1061/9780784483961.077

Poster and presentations:

- "Automated Building Inspection for Thermal Anomaly Detection and 3D Reconstruction Using a Drone-based Approach". Systems and Technologies for Remote Sensing Applications Through Unmanned Aerial Systems (STRATUS) 2022 Conference, Syracuse, New York, USA. 5/25/2022. Best Poster Award.
- "Drone-based scanning technology for characterizing the geometry and thermal conditions of building enclosure system for fast energy audit and design of retrofitting strategies". 6th Residential Building Design & Construction Conference (RBDCC). 5/12/2022
- "Automated Vision-Based Building Energy Assessment Using Drone Thermography". ASCE Construction Institute (CI) and Construction Research Council (CRC) Joint Conference, Arlington, Virginia, USA. 3/10/2022

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