3D as-is building energy modeling and diagnostics: A review of the state-of-the-art

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3D as-is building energy modeling and diagnostics: A review of the state-of-the-art

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Abstract

To achieve ambitious cuts in energy consumptions of the building sector, recent efforts have focused on devising methods that can provide accurate representation of the as-is conditions for existing buildings and in turn increase the quality and effectiveness of building retrofits. Today, 3D geometrical models produced by computer vision and laser scanning methods can be used as the basis of energy modeling purposes. Several methods are also introduced to facilitate the diagnostics and measurement of the thermal and other environmental conditions. To this end, this paper extensively reviews the state-of-the-art techniques that can semi-automatically or automatically create as-is geometrical and thermal models for building energy modeling and retrofit assessment purposes. It also provides an overview on the main algorithms used by these methods for representing spatio-thermal point clouds, automatically converting these point clouds into semantic Building Information Models (BIM) in gbXML format for as-is energy modeling purposes, and also contrasting them with expected energy performance models. The underlying formulations and methods for measuring actual thermal resistance of the building assemblies and mapping them into gbXML-based representations are also presented. The most recent works in the IT-driven building automation system (BAS) for energy conservation purposes are also reviewed. Finally, the technology gaps that need to be addressed in future research are identified and discussed.

1. Introduction

The building sector accounts for 41% of the primary energy use in the United States which is greater than the transportation and industrial sectors [1,2]. 22% and 19% of this energy use is consumed by residential and commercial buildings respectively [2], where a vast majority is still produced using non-renewable resources such as fossil fuels. With the rising demand for fossil fuel and the concerns about the impact of greenhouse gases on the climate, it is essential to find ways to increase efficiency, reduce loads, and utilize renewable fuel resources in buildings. Particularly improved efficiency of existing buildings through building retrofit and other measures represents a high-volume, low-cost approach for reducing current energy use and greenhouse gas emissions.

One of the main challenges in reducing the energy use in existing building is devising methods that can characterize and provide accurate representation of the as-is conditions [3,4]. This is important as without accurate representation of the as-is conditions, choosing from an array of expensive products and services with long and uncertain payback periods for retrofit purposes will be very challenging.

Over the past few years, a number of virtual auditing tools have emerged that support homeowners and energy auditors in their retrofit decision making processes. Nevertheless, their application requires large amounts of input data on the as-is conditions which is often not readily available. Generating such information and keeping them updating for existing buildings is also not easy [5]. The challenges of the current methods in representing as-is conditions, and the lack of integration between data from these methods and auditing tools, are both among the critical barriers for analyzing building energy performance and considering opportunities for improvements. These barriers, which are further discussed in the following sections, increase the risk of investments and minimize opportunities for large scale energy reductions.

1.1. The current workflow of as-built 3D modeling for existing buildings

Characterizing and representing the as-is conditions in existing buildings for retrofit assessment purposes typically involves two sequential steps: (1) modeling the underlying geometry in 3D and (2) measuring and assessing the environmental and thermal conditions. Despite their importance, an accurate 3D geometrical representation is not easy to achieve. This is because 2D plans are simply not available for many existing buildings. Even when these drawings are available, they may not exhibit all changes due to various cycles of renovation.

Over the last decade, the absence of accurate 3D models for energy modeling purposes and also other engineering applications created an opportunity to leverage sensing technologies such as laser scanning and photogrammetry techniques to reversely engineer the geometric modeling of the built environment. The process of generating 3D models from point cloud data and using them for energy modeling purposes consists of three sequential steps: data collection, modeling, and analysis. In today’s practice, these steps are performed manually by surveyors and energy auditors. Manual execution of these tasks can be time-consuming, expensive, and is often prone to errors [6–9]. While the analysis stage is fairly quick, taking several hours to complete, data collection and modeling are the bottlenecks of this process. The data collection can spread over a few days, nonetheless the modeling stage can span over multiple weeks or even months. These challenges have restricted the applicability of as-built modeling primarily to high profile projects. Thus, there is a need for low-cost, reliable, and automated methods for as-built 3D modeling. Such methods should quickly generate and update accurate and complete 3D semantically-rich models in a master format that is translatable to any energy modeling environment and can be widely applied across a large range of building categories [6].

1.2. Current intrusive approaches for measuring actual thermal energy performance

Measuring and assessing the environmental and thermal conditions in existing buildings is as challenging as representing their 3D geometry. Wang et al. [10] identified that the current challenges are in particular related to the lack of the following: (1) adequate measurements integrated with intelligence for evaluating component performance, (2) metrics and measurements for evaluating overall building performance, (3) tools and information geared to non-expert decision makers (e.g., owners, occupants), and (4) evidence that buildings audited for energy performance actually perform better after certain retrofits.

Today, thermography is widely used for effective communication of the as-is energy performance in existing buildings to homeowners. In the context of building energy diagnostics, thermographic inspection is now the dominant technique for detecting, analyzing, and reporting thermal defects. Despite documented benefits, the current practice of thermography is still based on the direct application of 2D thermal images. This practice has several inefficiencies that require further research.

(a) Collecting and analyzing a large number of unordered and nongeo-tagged thermal images with low spatial resolution is challenging [11]

Compared to consumer-level digital cameras (>1 megapixel), thermal cameras have lower spatial resolutions ranging from 160 120 to 640 480 pixels. They also exhibit smaller fieldsof-view due to inherent imperfections of the thermal lens. Consequently, sensing thermal performance in a typical building requires large numbers of thermal images to be collected during a thermographic inspection. The manual analysis of these large numbers of thermal images can also be time-consuming and labor-intensive. Because these images are typically unordered, uncalibrated, and are not geo-tagged, it is not trivial in the postanalysis stage to figure out ‘where these images are captured from or what building elements they are representing’. Given large numbers of thermal imagery for the purpose of entire energy diagnostics, such examinations can be expensive as well.

(b) Current assessments are primarily qualitative and do notaccurately characterize performance problems [12]

In the current practice of thermographic inspection, the analysis of performance problems is primarily based on auditors’ interpretation of surface temperature in thermal images (e.g. identifying hot or cold spots). Thus, the auditor’s knowledge and experience has an undoubtful impact on the quality of the assessments. Without a proper benchmark for building energy performance, such interpretations can be prone to errors as well. This is because the surface temperatures alone do not explicitly illustrate the energy performance problems. Moreover, considering the limited number of energy auditors, current practices are likely to be inconsistent, which can also adversely impact the quality of the inspections.

A breakthrough innovation in measuring as-is building thermal energy status through an easily accessible and understandable form for the retrofit decision makers is necessary to meet these challenges. To this end, this paper discusses the issues of current energy performance analysis practices for existing buildings and reviews related state-of-the art methods and technologies.

2. Reviews of the state-of-the-art practice

2.1. State-of-the-art practices

The following reviews the traditional and more recent virtual audits for building diagnostics and implementing energy-efficiency measures.

2.1.1. Traditional energy audit

To document the current workflows for energy auditing, the authors conducted several face-to-face and phone interviews with actual domain experts in the U.S. The subjects had 2–10 years of experiences in energy auditing. The following presents the best practices based on these interviews.

For residential buildings under construction, the energy auditing process is typically led and conducted by RESNET (Residential Energy Services Network) certified HERS Raters (Home Energy Raters) recognized by the U.S. federal government agencies such as the U.S. Department of Energy, the

U.S. Environmental Protection Agency and the U.S. mortgage industry [13]. The process involves two sequential steps: a pre- and a post-drywall installation inspection. This process particularly involves sealing inspection, infrared (IR) thermal imaging with post-depressurization, a blower door test for exploring envelope airtightness, and finally a duct blaster test for detecting duct leakages. Then, commercial software packages such as REM/Rate [14] are used to estimate the energy consumption in the building and finals reports are compiled together.

The process of auditing new buildings – primarily for commissioning purposes – is different from that of the existing buildings. Prior to inspection, the energy auditors meet with the homeowners several times to define the scope of the auditing process. Then an onsite audit is conducted which takes 2–2.5 h and typically costs $350 for a typical residential building. This audit mostly involves visual inspection using a thermal IR camera and an optional blower door test. Recommendations are made by offhand calculations based on the historical renovation costs from industry’s best practices, and no dedicated software is used to estimate the cost associated with potential savings from retrofitting the detected energy problems. For each building element, the actual thermal resistance – R-value which is key to an accurate representation of the as-is conditions – is estimated using on a comprehensive lists of R-values associated with various types of building materials. When necessary, these values are adjusted to account for degradations due to deteriorations or improper installations. Once the auditing process is complete, a report is generated using commercial software such as HomeGauge [15]. The estimated parameters are then placed into such software templates, and the results are distributed online or through hard copies. The completed auditing reports are ultimately handed directly to the homeowner.

2.1.2. Virtual audit

The current virtual auditing tools assemble meter data, weather information, GIS mapping, information about similar buildings, and other publicly available information for auditing purposes, and thus does not involve onsite inspection of the facilities [16]. Fig. 1 shows an example of online user inputs for virtual audit of a residential building. Once the data analysis is conducted, the tool provides recommendations on where implementing energy efficiency measures should be focused so that they can deliver the greatest impact.

The virtual audit is faster and cheaper than the traditional auditing methods. Nevertheless, it does not involve onsite field data measurement, and thus cannot specifically localize problematic areas for retrofit purposes. For example, using the feedback from the virtual audit, it is not possible to identify and localize which window or door suffers from thermal efficiency problems. Also, because most home owners have very limited expertise in assessing energy performance regarding architectural/structural and building systems, they can possibly provide less accurate data as input to a virtual auditor. Under these conditions, the assessment results may be less reliable.

3. Reviews of the state-of-the-art methods

3.1. Digital and thermal cameras

To address the limitations associated with manual data collection and analysis of large numbers of 2D thermal images, research has focused on methods that can automate each step or the entirety of the process [11]. Based on their contributions to data collection, analysis or both, these methods can be categorized into the followings.

3.1.1. Methods that facilitate ‘‘collection’’ of large number of thermal imagery

Essess. Inc [17] are among the first that developed an imaging system that streamlines the process of collecting thermal images from building envelopes. Their method relies on collecting large numbers of overlapping thermal images at night from an array of thermal cameras mounted on a car (see Fig. 2a). Using these images, a high-resolution panoramic thermal image of the building façades is generated (see Fig. 2b). This image is later used to assess the performance of the building envelopes. The method scales well to a street level, yet cannot easily document the performance of an envelope from inside of a building. In addition to ground-based collection of thermal images, the application of thermal cameras mounted on unmanned aerial vehicles is also proposed recently [18].

3.1.2. Methods that ‘‘create’’ 3D building thermal profiles

Over the past decade, the computer vision community has made significant progress on image-based 3D reconstruction procedures that can semi-automatically or automatically generate 3D models from unordered collections of photographs. These breakthroughs are in part to the advancements in feature detection and matching techniques that allow large collection of images to be analyzed and formed into tracks that can be fed into photogrammetry 3D reconstruction procedures. Several variants of these image-based reconstruction methods are used to

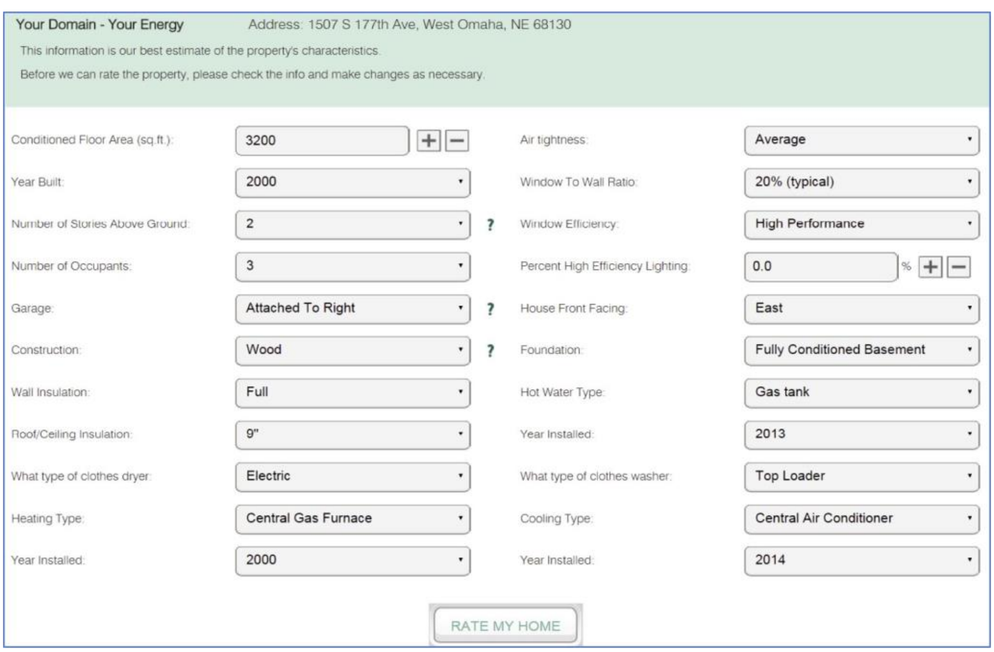

Fig. 1. An example of online user inputs for virtual audit of a residential building (image courtesy of MyEnergydomain.com).

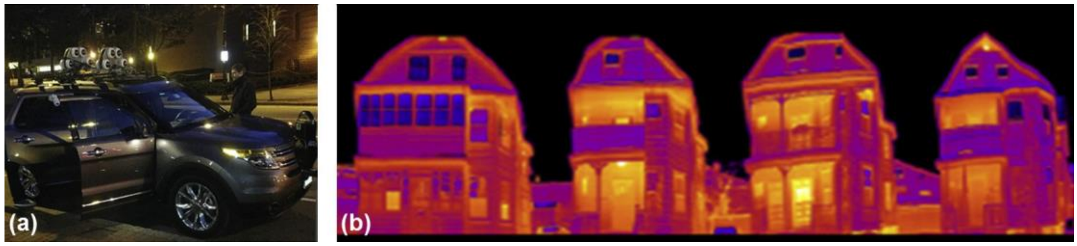

Fig. 2. (a) Vehicle-mounted thermal cameras. (b) An example of a panoramic thermal image of several building façades [17].

semi-automatically or automatically generate 3D thermal profiles for building envelopes and interior spaces.

Lagüela et al. [19] is one of the earlier examples on application of these methods. In their work, a method based on image fusion and matching is proposed to generate 3D thermal profiles for building exteriors. Thermographic mosaics are initially fused with their corresponding digital images. The fused images are then used as input to the Photomodeler Scanner [20] which is an imagebased 3D modeling software. Here, the overlapping areas between pairs of consecutive thermal image are manually selected by the user to initialize the area-based image registration procedure. In their method, during feature matching process, the user has to manually remove the false matches through a visual verification procedure. González-Aguilera et al. [21] is another example of modeling the thermal profile of a building façade in 3D using thermal imagery. In their work, the Photogrammetry Workbench (PW) software is used for reconstruction purposes. By feeding a collection of overlapping thermal images and thermal camera calibration information, the 3D thermal models and ortho-thermographs are produced for building façades under inspection.

Leveraging the pipeline of Structure-from-Motion (SfM) [22] and Multi-View Stereo (MVS) algorithms [23] for 3D reconstruction, has minimized the need for manual feature detection and matching, removal of false matches, and providing exterior camera calibration information. This pipeline is now commonly used in the computer vision community and can be considered as a candidate method for producing 3D thermal point clouds from a collection of overlapping thermal images. Nevertheless, direction application of feature detection and matching techniques on thermal images does not produce enough pairs of matched visual feature points that could be used for 3D reconstruction purposes. Ham and Golparvar-Fard [11] conducted several experiments to investigate the performance of commonly used feature detection and matching algorithms including Scale Invariant Feature Transform (SIFT), Affine-SIFT (ASIFT), and Speeded Up Robust Feature (SURF) for large numbers of unordered thermal images (Fig. 3). However, unlike their applications to a set of digital images, these algorithms exhibit poor performances in detecting and matching features across thermal images.

Fig. 3(b) and (d) shows 159 and 236 detected SIFT keypoints while (e) highlights 20 matched keypoints between the pair of overlapping thermal images (a and c) that look at the same area in the building environment. This is mainly attributed to the inherent characteristics of thermal images. Thermal images capture the subtle variations of the surface temperatures and represent them using color gradients. This typically smoothens sharp changes of intensity in the captured images (see Fig. 4). These characteristics impede direct application of feature detection and matching methods on unordered collection of thermal imagery which are the key components of the SfM procedure.

Ham and Golparvar-Fard [11] also conducted additional experiments to investigate the possibility of matching features from unordered collection of thermal and digital imagery and then leverage formulation of Epipolar geometry to produce 3D point clouds. Nevertheless, the limited number of features matched across unordered pairs of thermal and digital images (Fig 3f and h) did not produce enough tracks of feature points that can be fed into photogrammetry optimization procedures. Fig. 3(g) and (i) shows 236 and 14,946 detected SIFT keypoints while (j) highlights 8 matched keypoints between the pair of digital and thermal images that were simultaneously captured from the same location. Beyond the small number of matching feature points even prior to enforcement of the Epipolar geometry – i.e. by fitting the Fundamental Matrix within a RANSAC loop – one can also observe a significant number of mismatches among these paired feature points.

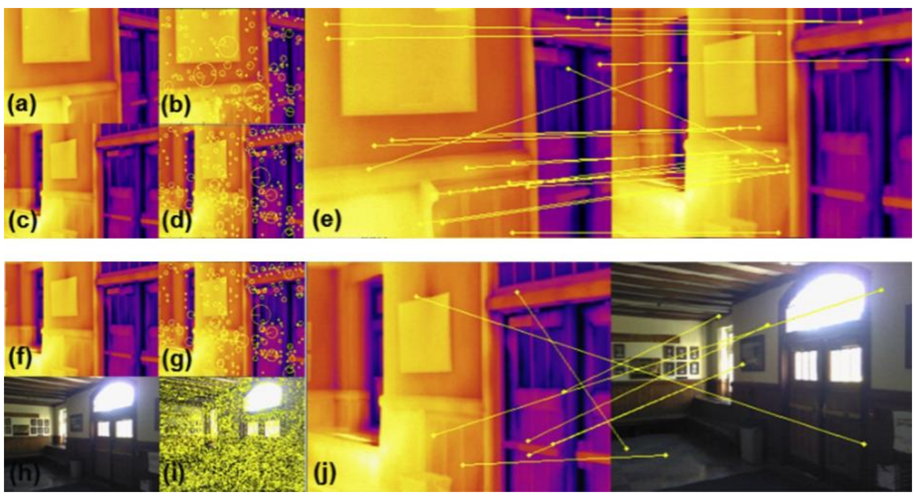

Fig. 3. Challenges in applying computer vision algorithm for feature detecting and matching between a pair of overlapping thermal images (Top), and a pair of digital and thermal images captured from the same viewpoint (Bottom) [11].

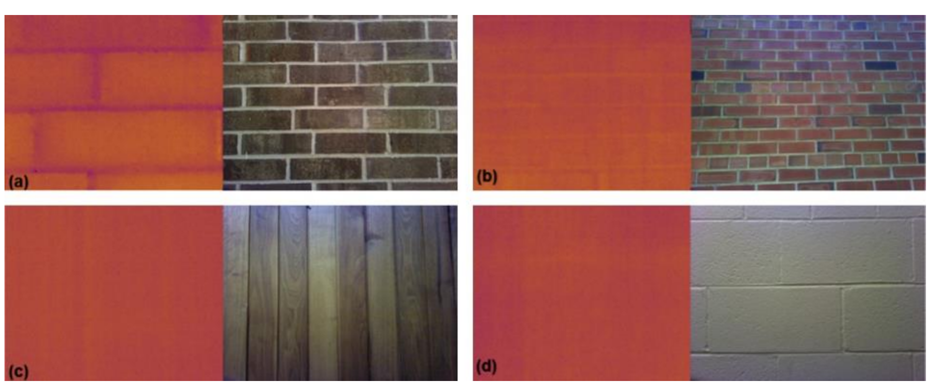

Fig. 4. Examples of thermal and digital images captured from different building surfaces, (a) exterior brick wall, (b) brick wall, (c) interior wooden wall, and (d) interior concrete masonry wall.

Another technical challenge here is that the variations of the building surface temperature in thermal images do not usually correspond to real-world textures/patterns depicted in digital images (see Fig. 4). This issue is exuberated when thermal images are captured from building interiors. Thus, the computer vision feature detection algorithms that search for pixels with higher intensity compared to their surroundings in the initially convolved images, do not return consistent feature points across corresponding thermal and digital images.

As an alternative to manual feature detection and matching, Ham and Golparvar-Fard [11] created and validated a new modeling procedure that automatically generates 3D spatio-thermal point clouds. The resulting spatio-thermal point clouds capture the actual surface temperature of building environments at the level of 3D points. Their method relies on leveraging pairs of digital and thermal images that are simultaneously captured with a consumer-level hand-held thermal camera. For each pair, the relative pose is calculated based on the formulation of the underlying Epipolar geometry. Then, the SfM procedure is directly used on the digital images to calibrate each built-in digital camera and estimate their pose (i.e., rotation and translation) in 3D. By leveraging the relative pose, the built-in digital camera calibration information from the digital images, and also calibrating the thermal lens, the camera calibration information is produced for all thermal images. The calibrated thermal images are then used in the Multi-View Stereo (MVS) algorithm to produce dense 3D thermal point clouds. Finally, the 3D thermal point clouds and the 3D building geometrical point clouds – which are the outcome of the SfM procedure on the digital images – are automatically superimposed. These models jointly form the 3D spatio-thermal point clouds. Fig. 5 shows two examples of these models that are produced for both exterior and interior of existing building. Here, the thermal and digital images are also localized within the 3D spatio-thermal model without the need for any location tracking module (e.g. GPS) to be attached to the thermal camera.

The image-based 3D reconstruction method introduced above is an offline process. In other words, an energy auditor has to take these images initially and then run them through the 3D reconstruction procedure. This process usually takes a few hours and unfortunately in the interim or even immediately after the data collection, the quality of the produced point clouds in terms of accuracy and completeness could not be verified. Despite following best practices to guarantee completeness and accurate during data collection, there could be parts of the point cloud that will remain incomplete or noisy. For instance, the flat featureless surface areas on drywalls will result in only a few measured temperature data in 3D. In addition, the resulting 3D point cloud can contain noise that will the reconstructed points to have a physical deviation from their associated building geometry.

To achieve a complete representation of a surface thermal performance or reason about the incompleteness of the 3D reconstruction procedure for a given scene, Golparvar-Fard and Ham

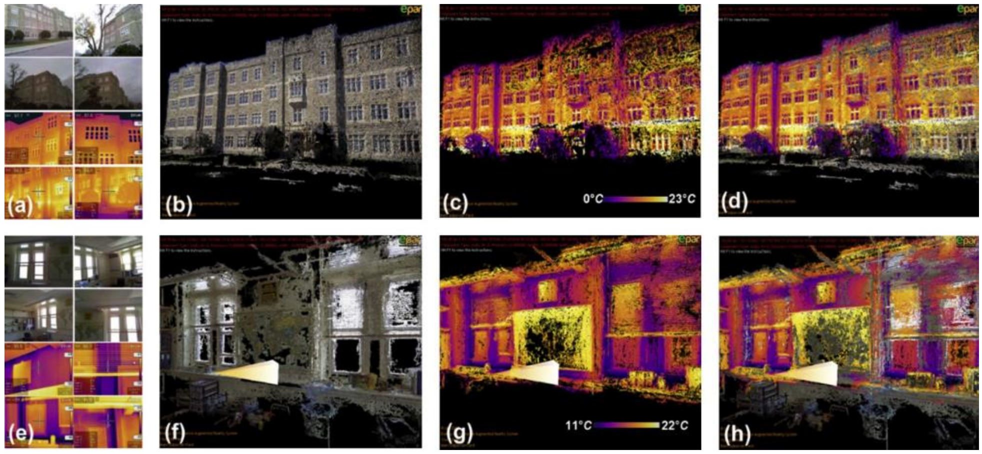

Fig. 5. 3D spatio-thermal point cloud of building environments, from left to right: Unordered digital and thermal images, 3D building point cloud, 3D thermal point cloud, integrated visualization [24].

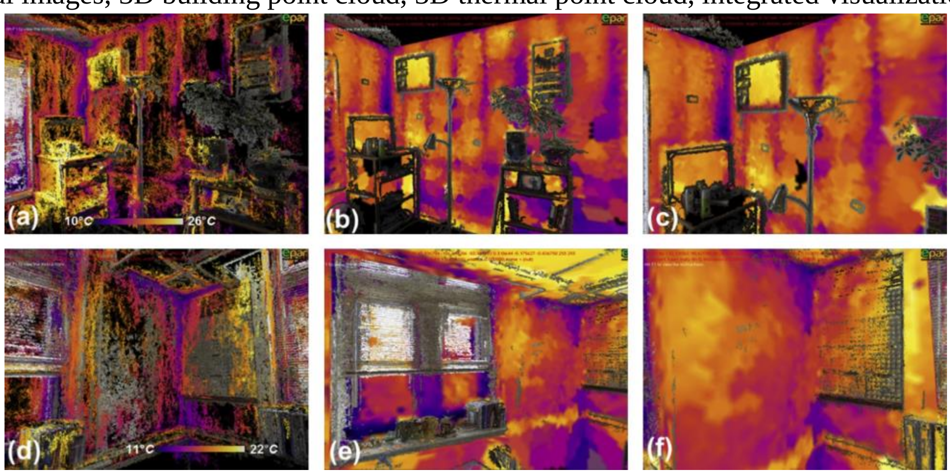

Fig. 6. 3D thermal mesh modeling of building environments [26,27], (a) and (d): 3D spatio-thermal point cloud, (b), (c), (e), and (f): 3D thermal mesh.

[25] proposed a method that converts 3D thermal point clouds into a corresponding 3D thermal mesh model. In this process, using boundary points extracted from the underlying building geometrical point cloud, a baseline mesh model is generated. The mesh and point cloud models are then transformed into a k-d tree structure, and the nearest neighborhood search is used to map the thermal values from the points in the cloud to the closest vertices in the mesh. This process improves the model completeness by extrapolating thermal performance for those areas that are sparsely reconstructed. Also, this process creates a uniformly dense point cloud by sub-sampling from those areas that are densely reconstructed. The outcome of this process is the 3D spatio-thermal mesh model wherein each vertex is associated with a temperature reading, averaged from all thermal images that observe that vertex during the energy auditing process (see Fig. 6).

3.2. Laser scanning and thermal camera

Laser scanning technology has long been used to create high resolution and accurate 3D as-built models of structures and scenes, typically with mm-level accuracy. There has been some efforts to map images taken from a thermal camera onto point clouds. Alba et al. [28] developed a bi-camera system consisting of Infrared (IR) camera, digital camera, and 3D laser scanner to acquire and integrate information for building diagnostics and restoration applications. The thermal data and the point clouds were fused by using control points that were measured manually by a digital camera and a laser scanner. Borrmann et al. [29,30] developed a 3D thermal modeling method using Light Detection and Ranging (LIDAR) and a low resolution IR camera (160 120 pixels) mounted on a mobile robot Irma3D to expedite scanning and registration processes. The thermal data were matched to the corresponding point clouds, which were automatically registered using the 6D simultaneous localization and mapping (SLAM) technique [31]. Due to the fixed camera configuration with the limited camera field of view, however, a tall building needs to be scanned from a far distance, which would result in low-resolution thermal data acquisition.

Lagüela et al. [32] also introduced methods for projecting thermal RGB data to the surface of meshed point clouds of a small building. Registration of thermal image and point clouds was performed through the extraction of 2D line features in the images and 3D line features in the point cloud, followed by feature matching and computation of the orientation parameters, parameterized as a combination of a rotation matrix and a translation vector. In their approach, the temperature differences were visualized using a color spectrum.

Wang and Cho proposed a unique way to non-invasively collect and analyze various energy performance data, from which broader context of analyzed information can be automatically extracted without disturbing the occupancy [10,33–35]. A prototype of the hybrid visual and thermal data collection system has been developed by Wang and Cho [10,33–35] which is shown in Fig. 7a. The hybrid system consists of multiple 2D line lasers, a thermal camera, and a digital camera, which simultaneously collect point clouds, RGB texture, and temperature data from the envelope of existing buildings. Temperature and texture data are automatically fused with corresponding points during the data collection process. A thermal scanned residential street model is shown in Fig. 7b. After registering all individual thermal point clouds, a window detection algorithm is applied to create virtual thermal points on transparent window glasses [10].

3.3. RGB-D and thermal cameras

The advent of new imaging systems such as Microsoft Kinect or Asus Xtion has made color and dense depth images readily available. There are great expectations among both researchers and practitioners that the development of such systems lead to a boost of new applications in the field of 3D perception for both structured and unstructured environments. Beyond providing geometrical information through dense depth imagery, these systems also have potential to produce the point clouds that are needed for spatio-thermal modeling purposes. Through joint calibration, they can also map surface temperatures captured from a thermal camera into their densely produced point clouds.

Vidas and Moghadam [37] is among the first to propose a 3D thermal modeling system. Their system called 'HeatWave' assembled together using an ASUS Xtion Pro Live RGB-D sensor and a thermal camera. In their method, the trajectory of the RGB-D sensor is first estimated, and then a 3D voxel model of the environments under inspection is continuously updated. This is done by conducting SLAM which is built on the work of Izadi et al. [38]. The overall process for 3D modeling consists of the following four steps [38]: (1) depth map conversion: the depth map is converted from the image coordinates into the 3D points in the camera coordinates; (2) camera tracking: using the Iterative Closet Point (ICP) algorithm, a transformation is calculated to align the current oriented 3D points with the previous frame; (3) volumetric surface representation: by using the global pose of the camera, oriented 3D points are converted into the global coordinates for updating a single 3D voxel grid; and finally (4) raycasting: RGB color values representing surface temperature and building geometry are assigned to the 3D model from multiple views for rendering purposes.

To leverage the outcome (the depth maps with temperature values) for comparing expected-vs.-actual thermal profiles, and also assessing thermal resistance in the built environment, Ham and Golparvar-Fard [39] have also conducted several experiments to generate 3D thermal mesh models using a 3D printed prototype that assembles a Kinect sensor and a GOBI thermal camera. Fig. 8 shows a snapshot of this platform. Fig. 9 also shows snapshots of the developed system. The depth information obtained from an RGB-D sensor (Kinect) is used to track the pose of the RGB + D + T (D: Depth, and T: Temperature) sensor in 3D and then reconstruct

3D models for representing the geometry of the underlying scene in real-time [38].

The intrinsic camera parameters for the thermal camera are calculated by using a one-time thermal camera calibration process. The relative pose of the thermal camera lens with respect to the digital camera lens of the Kinect is derived to estimate the extrinsic thermal camera parameters. Finally, the thermal information collected from 2D thermal images is texture-mapped on the 3D geometrical mesh model. Fig. 10 shows the preliminary results of 3D thermal mesh modeling using a RGB + D + T sensor.

3.4. Creating as-built BIM for energy analysis purposes

The documented benefits of BIM for streamlining the construction and operation of buildings have increased its popularity for energy modeling purposes. BIM – produced with authoring tools such as Autodesk Revit – can be the input to building energy analysis tools and provide the necessary building information for energy modeling purposes. Extracting notional thermal property of the building elements from BIM is another added value of leveraging these models for modeling energy performance particularly for new buildings. However, the direct application of BIM with preloaded notional thermal properties for elements in existing buildings is challenging. This is because the heat transfer condition of the building elements is gradually degraded during the operational phase. Without considering such diminishing thermal properties in BIM, BIM-based energy analysis for existing buildings is likely to yield inaccurate results. To address this limitation, recent research has introduced methods for BIM with as-is conditions in gbXML format from point clouds and images that can be categorized as follows.

3.4.1. Automated reconstruction of BIM from LIDAR’s point clouds

To calculate the proposed thermal performance estimation algorithms (e.g., R value and cost savings), it is important to classify the building envelope components as individual objects and reconstruct and recognize them in as-is 3D geometry. For example, the size of window is needed for thermal cost estimation. The current state-of-the-art reconstruction commercial software packages such as Leica’s CloudWorx, ClearEdge3D, Trimble’s RealWorks, Autodesk’s Plant 3D, and Kubit’s PointSense provide semiautomated 3D model extractions functions, but still need manual object recognition and selection. Dimitrov and Golparvar-Fard also proposed a method for fitting NURBS surfaces into automatically automated point cloud models for generic modeling purposes [36].

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For the fully-automated reconstruction of various shapes of building envelops from point clouds, Cho

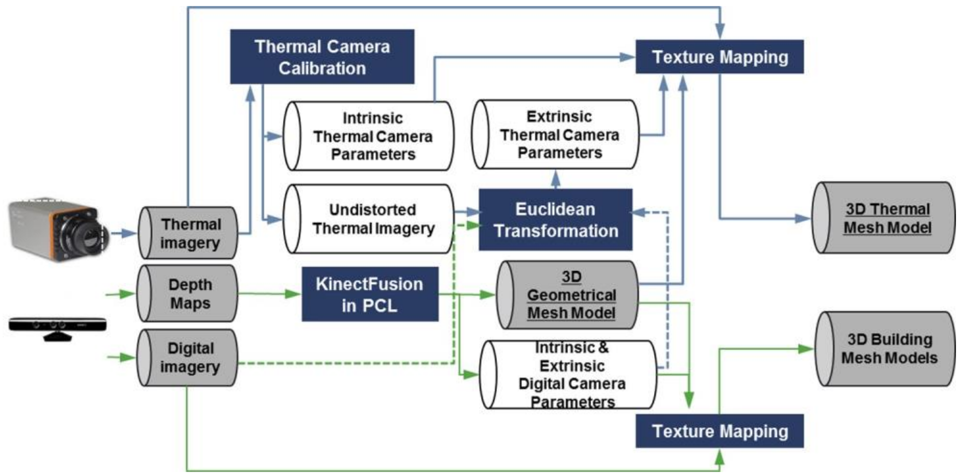

Fig. 9. Data and process for 3D thermal mesh modeling using a RGB + D + T sensor [39].

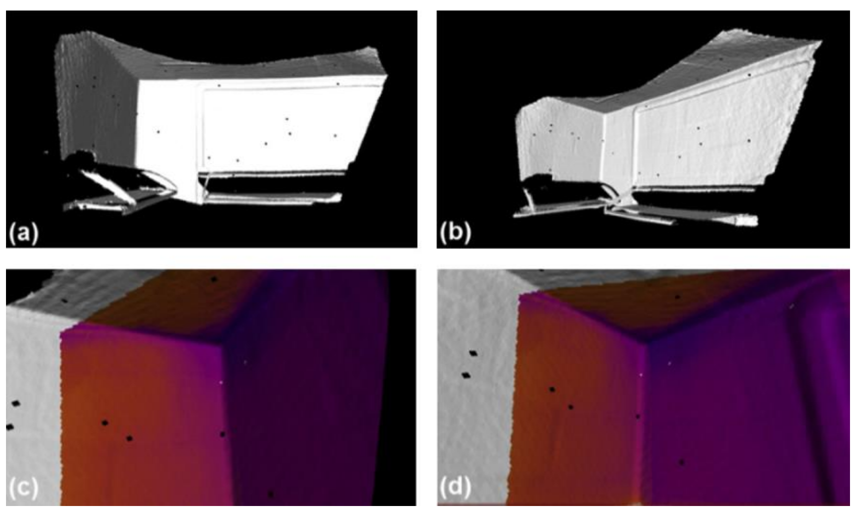

Fig. 10. (a) and (b) 3D geometrical mesh model, (c) and (d) 3D thermal mesh models texture-mapped with the associated thermal images using a RGB + D + T sensor [39].

and Wang [33] demonstrates the concept of an automated reconstruction of a building information model in gbXML format for a house from the complete point-cloud scan data. Recently, Wang and Cho [34] introduced a fully automated building envelope reconstruction and modeling algorithm from raw point clouds. Fig. 11 shows the process of automatic extraction of semantic BIM objects from a point cloud. The extracted semantic BIM model is further processed to semi-automatically create thermal zones if floor plans are available. Finally the building and thermal zones can be exported to most of the energy simulation tools which generally accept the gbXML file format [35]. Fig. 12 shows an example of created thermal zones of a residential building after exported to ECOTECT energy simulation tool.

3.4.2. Image-based thermal BIM reconstruction

Lagüela et al. [44] proposed a method for associating actual thermal property measurements based on surface temperature sampling in 2D thermal imagery to their corresponding entries in gbXML schema. The workflow involves several manual steps for identifying the BIM elements relevant to each measurement and updating their thermal properties in the gbXML entry. Given large number of BIM elements, this process can be labor-intensive and will be more prone to error. To streamline the process, Ham and Golparvar-Fard [27] proposed an automated method for updating the thermal property of BIM elements based on the as-is building conditions. In terms of thermal performance, this shortens the gap between the architectural information in the as-designed BIM and the as-is building conditions. The proposed method maps thermography-based R-value measurements at the level of 3D points to the corresponding building elements in BIM. This is done by searching for the nearest 3D thermal points with respect to each vertex in meshed BIM that the building elements in gbXML-based BIM are discretized into a mesh. Then, their corresponding entries for thermal properties in gbXML schema are automatically updated based on the XML Document Object Model (DOM). By using the updated gbXML-based BIM as an input of BIM-based energy analysis, practitioners can more reliably model the current energy performance of existing buildings. This has potential to improving analyses on different retrofit alternatives during decision-making processes.

3.5. Heat resistance or other thermal value estimation methods for building envelopes

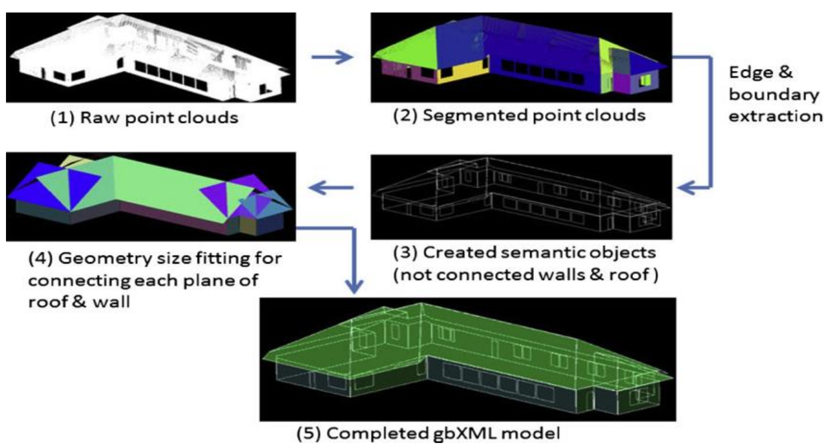

Fig. 11. The process for automatically extracting building envelope elements from a point cloud of a bank facility.

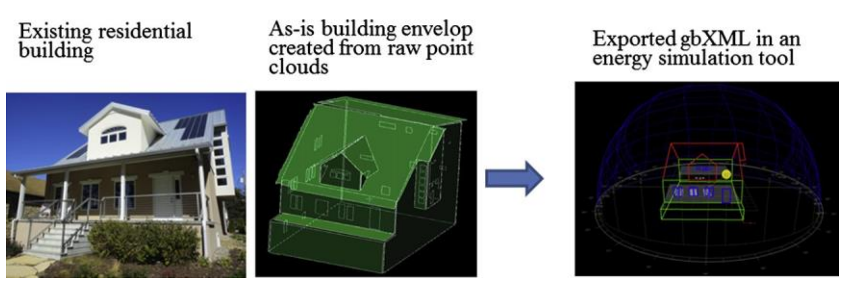

Fig. 12. Extracting and converting BIM envelope to thermal zones in an energy simulation program [35].

An envelope is defined as the building exterior thermal insulation components, including exterior walls, a roof, windows, doors and a basement floor. Due to the gradual degradation of the building envelopes during their lifecycle, the actual thermal resistances of the building assemblies typically become lower than the theoretical value declared by their manufactures. The poor performance caused by these changes results in an increase in the operational frequency of heating and cooling systems to recover the unnecessary heat transfer. As such, exploring temporal variation in the as-is thermal properties of building envelopes is critical to building energy audits. Considering a steady state condition of heat transfer in building environments, thermal resistances (Rvalue) can be described with the following equation [26,40–44]:

$$R = \frac{Area \times \Delta T}{dQ/dt} \tag{1}$$

where dQ=dt is the overall heat transfer rate through the area of a building surface (Area), and DT is the temperature difference between building inside and outside. Here, by assuming that sources of indoor heat transfer consist of the thermal convection (Eq. (2)) and the thermal radiation (Eq. (3)), R-value can be describe by using the Eq. (4).

$$Q_{Convective} = \alpha_{convective} \times Area \times |T_{inside,air} - T_{inside,wall}| \tag{2}$$

$$Q_{Radiation} = \varepsilon \times \sigma \times Area \times \left|T^4_{inside,wall} - T^4_{inside,reflected}\right| \tag{3}$$

$$R = \frac{|T_{inside,air} - T_{outside,air}|}{\alpha_{con} \times |T_{inside,air} - T_{inside,wall}| + \varepsilon \times \sigma \times \left|T^4_{inside,wall} - T^4_{inside,reflected}\right|} \tag{4}$$

where a$_{con}$vective is the convective heat transfer coefficient, e is the thermal emissivity, and r is the Stefan–Boltzmann constant. The indoor temperature ($T_{inside;air}$) and the outdoor temperature ($T_{outside;air}$) are measured by using a thermometer during the thermographic inspection. The reflected temperature ($T_{inside;reflected}$) can be measured using a small crumpled aluminum foil stitched to an interior building surface. Aluminum foil has low emissivity and high reflectivity which can serve as a great alterative for measuring these properties.

Based on Eq. (4) and using surface temperature data ($T_{inside;wall}$) obtained from 2D thermal images, several studies have focused on measuring the actual R-value or U-value (which is a reciprocal of an R-value) [40–43]. These studies mainly leverage thermal images with low spatial resolution and small fields-of-view. Thus, they encounter the same challenges of the scanning methods introduced in Section 1.2 regarding scalability. This impacts their direct application for building energy auditing purposes. To address this limitation, Ham and Golparvar-Fard [26] proposed a method that measures the actual R-values at the level of 3D points by using 3D surface temperature data ($T_{inside;wall}$). Such data is queried from the 3D spatio-thermal model produced through imagebased 3D reconstruction procedures. Their work discusses the challenges in assuming that a confined sampling measurement of the thermal resistance from 2D thermal imagery is a good representative of an entirety of a building element. Instead, the method presented in [26] measures the actual thermal resistance at the level of 3D points so that the non-uniform deteriorations of the actual heat transfer conditions can be better characterized across the surface geometry of the building elements.

3.6. Identification of potential performance problems by contrasting expected and actual energy performance models

The energy performance obtained from simulations using asdesigned building conditions typically deviates from the actual energy performance which reflect the actual as-is building conditions. Analyzing such deviations can identify building areas associated with potential performance problems and validates simulation models for calibration purposes.

Ham and Golparvar-Fard [24] created a method for Energy Performance Augmented Reality (EPAR) modeling which jointly models and visualizes actual and expected thermal performance of building environments in a common 3D environment. Their method identifies and quantifies the building energy performance deviations. For modeling, their method leverages: (1) an computer vision-based 3D spatio-thermal reconstruction to generate actual thermal performance models and reflect the as-is building conditions [11] and (2) a numerical analysis to simulate the expected thermal performance of the as-designed building environments.

Using these EPAR models, Golparvar-Fard and Ham [25] proposed an automated method to (1) calculate deviations between actual and expected thermal performance in building environments; (2) detect potential performance problems based on the calculated deviation and a predefined threshold value; and finally (3) visualize the detections along with the corresponding geometrical characteristics in 3D. Fig. 13 illustrates two examples of detected potential performance problems based on energy performance deviations in the EPAR models.

3.7. IT-driven building automation system for high performance building

In addition to the retrofit analysis through as-built envelope thermal models, it is important to understand and improve performance of the existing building systems. In this context, the thermal diagnostics of the building envelope in 3D can provide useful input for operation and control of the existing heating and cooling systems. For example, based on the measured actual R-values for each thermal zone, heating and cooling loads can be more efficiently applied to provide a uniform comfort temperature for each building zone.

Building Automation Systems (BAS) are centralized, interlinked, networks of hardware and software, which monitor and control the building facilities. While managing various building systems, the automation system ensures the operational performance of the facility as well as the comfort and safety of building occupants [45]. Such control systems and smart sensors can be installed in existing buildings.

Using the BAS concepts, several efforts have been made to provide a robust information technology platform to deliver more energy savings in a more efficient manner without compromising the quality. The National Science Foundation (NSF) and the Federal Highway Administration (FHWA) in the U.S. encourage and support the utilization of cyber physical systems (CPS), which are engineered systems that interconnect physical infrastructure with cyber networking systems. Peng et al. [46] discussed an application of CPS for building energy management based on a semicentralized decision making methodology. This application can be realized by fusing and analyzing data for real-time energy system monitoring, prediction and control. Simmhan et al. [47] developed a cloud-based software platform for the Smart Grid Cyber Physical System. Along with the development of data-driven analytics, it supports demand prediction and efficient, sustainable management of energy by utilizing their dynamic demand response optimization over a cloud technology. Beloglazov et al. [48] discussed potential ways to reduce the power consumptions of computing data center as well as the CO2 emissions.

There has been much research, with the use of sensors that potentially provide better control over utilities, such as artificial lights and HVAC devices. Dodier et al. [49] and Dong et al. [50] conducted research for space occupancy determination and occupancy detection, respectively, expecting extension of such research to a variety of building technology, such as improved building operations. A vision-based system [51] was proposed for human detection and activity characterization, which offers potential ways of more efficiently controlling and managing the building management systems. Smart occupancy sensors [52] and RFID based occupancy system [53] were proposed to more effectively and adaptively control the lighting system. Li et al. [54] used an RFID system to detect human occupancy in buildings to support demand-driven HVAC operations. A thermostat is one of the most recently developed technologies with utilization of sensors. A variety of versions of thermostats is available to wirelessly and/or automatically control a heating or cooling system to maintain a desired temperature.

In an attempt to reduce the energy consumption of the entire building, many products have been investigated and produced to control the temperature at an individual occupancy level. Wristify is one of these example [55]. This bracelet can be worn by a person on wrist and in turn enhance the thermal comfort of the occupant. Personal comfort systems with fans and foot warmers are also recently developed [56]. These systems can be equipped with sensors and are typically connected to smart phones to allow for flexibly control of the environment and result in energy savings. Other existing local thermal management systems include evaporative coolers, air-conditioned jacket, cooling vest, personal environment module, and ductless task air conditioning. These, however, have their own disadvantages and the spread of these systems are not yet desired. The disadvantages include poor performance, low efficiency, high cost, poor aesthetics, and location specific sensitivities causing noise, immobility and thermal asymmetry.

A cloud-based open and transparent platform enables a paradigm shift within the marketplace for building products and services that will provide decision support for empowering all stakeholders while connecting end-users directly to product and service providers. This platform interacts with devices, appliances, and equipment in the home through low-cost home automation hardware and software; and provides intuitive decision support software through cloud computing technologies to engage and empower stakeholders to pursue energy and environmental solution. It also offers innovative building energy efficiency products, technologies and services. Publicly available data can be collected using data mining algorithms including building codes, building description, and local weather history. In addition, smart sensor data (if installed) and user input data (e.g., retrofit history, updated HVAC information) can augment the database.

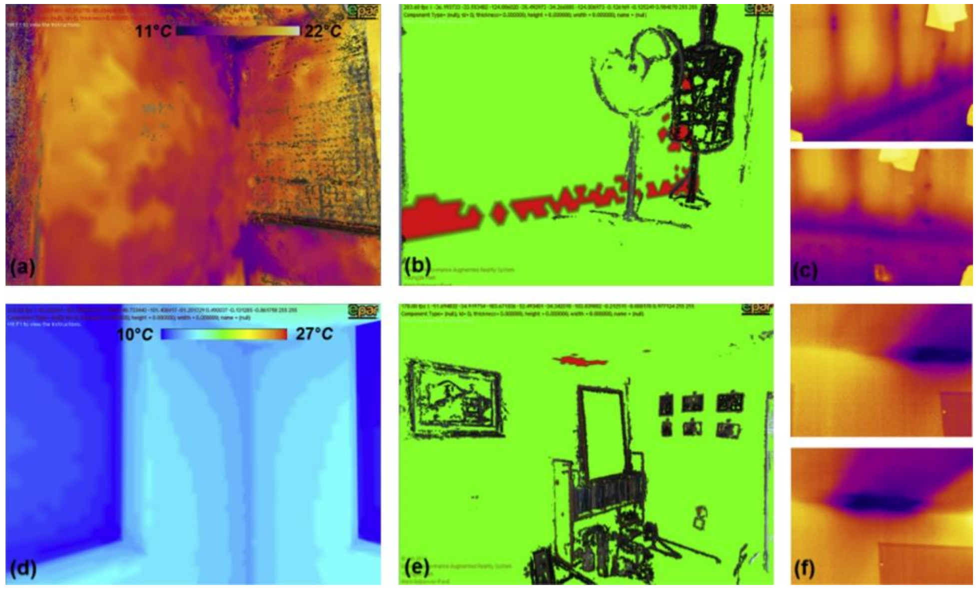

Fig. 13. (a) Actual thermal performance, (d) expected thermal performance, (b) and (e) examples of potential performance problems detected in EPAR models, (c) and (f) thermal images representing the detected building areas [25].

4. Roadmap for short-term and long-term research

While significant progress has been made over the past few years to create solutions for building diagnostics purposes, there are a number of research challenges that have remained open. The opportunities for future research are as follows:

4.1. Challenges and opportunities for improving as-is building geometric modeling

The current representation of the building geometry in the latest gbXML schema is still limited. For example, the current gbXML schema only supports a 2D rectangular polygon and a 3D planar polygon, which are not yet standardized for all building geometry. Curved features (e.g., circular window) need to be approximated with multiple planar polygons. Although prior works on converting a point cloud to semantic 3D models in gbXML schema present promising results, more research needs to be conducted to solve such modeling challenges for representing geometrical conditions in existing buildings.

Guaranteeing completeness in generating 3D spatio-thermal models remain another open challenge. None of the state-of-theart solutions can provide real-time feedback to the users to make sure the models produced for as-is representations are complete. Although promising results are shown by using RGBD cameras, yet testing such solutions at the scale of a building and validating their accuracy remains a challenge. In addition, the RGBD approach is limited to indoor geometric modeling.

4.2. Challenges and opportunities for improving thermal performance measurements

Static occlusions (e.g., large furniture or fixed wall frames) around walls during indoor thermographic inspections continue to be a challenge in achieving reasonable accuracies in building diagnostics. To minimize the impact of static occlusion for accurate analyses of building surface thermal performance, energy auditors currently encourage homeowners to take away as many objects as possible before inspection. Despite their significance, in most occupied buildings, it is not possible to remove all objects that block the line-of-sight to building assemblies either due to space limitations or because of the immobility of the attached objects on walls such as fixed wall frames. Since IR thermal cameras are incapable of detecting thermal performance from the interior building surfaces occluded by objects, segmentation of non-relevant objects from the reconstructed 3D scene and extrapolation of thermal performance for the occluded surfaces still remain as open research challenges.

Another prevalent challenge for reliable thermographic inspection is that a steady-state condition of heat transfer need to be formed in the building environments under inspection [12,41,43]. However, in practice, it is not easy to maintain such ideal heat transfer condition during whole thermographic inspection periods (e.g., takes around 2–2.5 h for a typical residential building). For outdoor measurement, it is recommended to collect thermal data of building envelope after midnight when the indoor living activities are most likely dormant, which would give a better steadystate condition of heat transfer. More research still needs to be conducted on how the thermographic inspection errors caused by a non-steady-state condition can be accounted for.

In summary, recent technology advancements have shown promising results in automating geometric building modeling and non-invasive thermal performance assessment processes from raw data including point clouds, images, and thermographic measures. Compared to the data processing methods, more difficult challenges that researchers are facing are how to collect the data necessary for accurate and complete diagnostics (e.g., avoiding obstacles, mining public data) and how to assure the quality of the collected data, which directly impact the reliability of the processed results (e.g., as-is geometric dimensions and R values). Thus, one possible direction for future research should focus on data collection methods and relevant strategies. More validation studies on current methods still need to be conducted.

5. Conclusion

This paper provides a comprehensive review on the recent research for geometric modeling and energy diagnostics for existing buildings. The state-of-the-art methods for providing an accurate as-is representation of the existing buildings both from their geometry and environmental condition perspectives are reviewed, and potential areas for improvements are thoroughly discussed. Further, the state-of-the-art BAS as a cloud software as a service (CSaaS) is reviewed. Despite significant improvements achieved over the last few years, several key areas that could be resolved with LIDAR and computer vision techniques remain open. The open research challenges are discussed in detail and a few directions for future research are provided.

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