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A semi-automated method for integrating textural and material data into as-built BIM using TIS

Asem Zabin[1a], Baha Khalil[2b], Tarig Ali[1c], Jamal A. Abdalla*[1] and Ahmed Elaksher[3d]

[1]Department of Civil Engineering, American University of Sharjah, Sharjah, UAE
[2]Department of Mathematics and Statistics, American University of Sharjah, Sharjah, UAE
[3]New Mexico State University, Las Cruces, New Mexico, United States of America

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Abstract. Building Information Modeling (BIM) is increasingly used throughout the facility's life cycle for various applications, such as design, construction, facility management, and maintenance. For existing buildings, the geometry of as-built BIM is often constructed using dense, three dimensional (3D) point clouds data obtained with laser scanners. Traditionally, as-built BIM systems do not contain the material and textural information of the buildings' elements. This paper presents a semi-automatic method for generation of material and texture rich as-built BIM. The method captures and integrates material and textural information of building elements into as-built BIM using thermal infrared sensing (TIS). The proposed method uses TIS to capture thermal images of the interior walls of an existing building. These images are then processed to extract the interior walls using a segmentation algorithm. The digital numbers in the resulted images are then transformed into radiance values that represent the emitted thermal infrared radiation. Machine learning techniques are then applied to build a correlation between the radiance values and the material type in each image. The radiance values were used to extract textural information from the images. The extracted textural and material information are then robustly integrated into the as-built BIM providing the data needed for the assessment of building conditions in general including energy efficiency, among others.

Keywords: As-Built BIM; building materials; thermal infrared imaging; thermography; texture extraction; feature technology; information visualization; machine learning

1. Introduction

Having a full record of information of a facility is essential as it helps in assessing building performance, managing building repairs, and renovations. However, full documentation of information of an existing building faces many difficulties and challenges. Until recently, documentation procedures are mainly done manually, which is tedious, time-consuming, labor-intensive, error-prone, and costly (Fadoul *et al*. 2017, Klein *et al*. 2012, Arayici 2008). Current methods for data acquisition at construction sites include laser distance meters, digital cameras,

*Corresponding author, Professor Jamal A. Abdalla, E-mail: jabdalla@aus.edu
[a] Formerly M.S. Student, E-mail: asemzabin@gmail.com
[b] Formerly M.S. Student, E-mail: baha@akrabawi.org
[c] Associate Professor, E-mail: atarig@aus.edu
[d] Associate Professor, E-mail: elaksher@nmsu.edu

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measuring tapes (Jung *et al*. 2014) and laser scanners (Klein *et al*. 2012, Ali et a. 2008) are gaining wide acceptance. In general, information about a specific building object that exists in reality might have not been recorded during construction or it might have changed since then. If this change is not verified, it will lead to unnecessary efforts, which can be costly and time-consuming. Previous research (Tang *et al*. 2010, Klein *et al*. 2012, Dimitrov *et al*. 2014, Wang *et al*. 2013, Armesto *et al*. 2009, Lagela *et al*. 2013) have addressed issues related to utilizing remote sensing technologies such as laser scanners to collect geometric information about an existing facility to create the BIM geometry. This method produced relatively accurate geometric databases that proved to be helpful in facility maintenance and space management. The information collected with a non-destructive, automated process such as remote sensing, stored in a BIM-compliant database also has many advantages for many facility management practices, such as commissioning and closeout, quality control and assurance, energy management, maintenance and repair, and space management (Alkadri *et al*. 2018, Volk *et al*. 2014, Abdalla *et al*. 2014). However, having a geometric-rich BIM is not enough to determine the condition of the facility without other important parameters that cannot be obtained by laser scanning such as textural and material information. Spectral properties of objects surfaces (e.g. interior walls) in terms of the amount of the electromagnetic radiation (EMR) reflected or emitted by them can be used to gather lots of information about them. This is because the amount of reflected, absorbed, transmitted, or emitted radiation depends on the nature of the material of the surface, the wavelength of EMR, texture, and the illumination angle (angle between the inward surface normal and the direction of EMR). The aim of this research is to extract material and textural information using infrared remote sensing technology and integrate that into the as-built BIM. This would help in creating an updated information-rich BIM database, which would be useful in building performance evaluation, energy analysis, energy management and water leaks detection in pipes inside interior walls.

1.1 As-Built BIM

Building Information Model (BIM) is a term that has become very common in the design and construction fields over the past 20 years (Fadoul *et al*. 2018, Abdalla *et al*. 2018, NIBS 2007a). BIM transformed building information documentation from paper-centric processes into a digital workflow to develop the 3D model and further learn about the architectural and structural attributes of building elements. This is used to simulate and employ reality-based models to manage the built environment within a fact-based, repeatable and confirmable decision process that minimizes risk and increases the quality of actions and products, industry-wide (Eastman *et al*. 2011). BIM is defined by the Charter for the National Building Information Model Standard, as an improved planning, design, construction, operation, and maintenance process using a standardized machine-readable information model for each facility, new or old, which contains all appropriate information about that facility in a format useable by all throughout its life cycle (NIBS 2007b).

There is a growing interest in the construction industry for the use of BIM in facility management (FM) for coordinated, accurate, and computable building information from the design to construction to maintenance and to operation stages of a buildings life cycle including rehabilitation. Creation of as-built drawings for a building is an essential stage of the building life-cycle as the other stages, such as planning, design, and construction (Volk *et al*. 2014). Successful management of operating facilities and infrastructure involves extensive, up to date, and accurate field records such as facility spaces, equipment, materials, and energy systems (Tang *et al*. 2010, Klein *et al*. 2012). During the design, construction, initial handover, and even operation stages, building documents undergoes continuous changes and updates. Documentation of this information is essential as it helps the owners and facility managers in assessing building performance, managing building repairs, and renovations (Gallaher *et al*. 2004). Today, full documentation of information faces many difficulties and challenges (Hara *et al*. 2019, Francis *et al*. 2019, Volk *et al*. 2014, Tang *et al*. 2010, Klein *et al*. 2012, Becerik-Gerber *et al*. 2012, Dimitrov *et al*. 2014). Information about a specific element that exists, in reality, might not be recorded or changed without being verified. Otherwise, the quality may drop without being noted, and these undocumented changes normally lead to unnecessary efforts and costs (Gallaher *et al*. 2004). A study by the National Institute of Standard and Technology (NIST) found out that the cost of inadequate interoperability of building information is very high for new construction and relatively high for maintenance (Eastman *et al*. 2011). Moreover, large amount of capital expenditures are lost every year in the United States due to the lack of information at construction sites for the maintenance and repair personnel (Becerik-Gerber *et al*. 2012).

There is an increasing demand to automate the building information acquisition and storing processes in order to support facility personnel in getting necessary information about buildings whenever needed (Cho *et al*. 2019, Lu *et al*. 2017, Tang *et al*. 2010). Furthermore, artificial intelligence techniques such as genetic algorithms and gaming were used by researchers for simulation and building information modeling integration (Sandoval *et al*. 2018, Kim *et al*. 2017). In response to the demand for more efficient as-built surveys, researchers are investigating the ways remote sensing tools and sensor networks can provide valuable information about the existing buildings such as geometry, elements location, materials, etc. (Abdalla *et al*. 1991, Tang *et al*. 2010, Klein *et al*. 2012, Volk *et al*. 2014).

1.2 Building information acquisition techniques

Over the past decade, multiple efforts by several researchers have been made to make computers acquire, understand, index, and interpret images expressing a wide variety of concepts, with much progress (Eastman *et al*. 2011, Santos 2017). The main challenges researchers faced include variable and sometimes uncontrolled imaging situations, complex and hard-to-describe objects in the image, objects occluding other objects, and conceptual information perceived by humans. Automatic image classification algorithms have been an important research topic for decades in fields such as development of image processing in space sciences, web searching, geographic information systems (GIS), bio-medicine, surveillance and sensor systems, commerce, and education (Eastman *et al*. 2011, Arayici 2008, Jung *et al*. 2012, Celik *et al*. 2018). Recent studies have given special attention to automated image retrieval based on texture. The common objective was to retrieve texture with high accuracy utilizing the least complicated computational approaches. The most popular texture extraction techniques that use multi-scale image representations are discrete wavelets, Gabor wavelets, dual-tree complex, Grey Level Concurrence Matrix (GLCM), and contourlets (Kottawar *et al*. 2014). All of these approaches fall under the spatial-frequency image transforms, where the image is decomposed into sub-images at multiple scales, frequencies and orientations of image details and structures using linear filter banks and down- or up- sampling operators (Smith *et al*. 1996).

Cho *et al*. (2015) provided a detailed review of several techniques that can semi-automatically create as-is geometrical and thermal models for energy modeling of buildings and retrofit assessment purposes. They also presented an overview of the main algorithms used by these techniques for representing spatial-thermal point clouds. Furthermore, they described how spatial-thermal point clouds can be converted into semantic BIMs in gbXML format for as-is energy modeling purposes. The fundamental formulations and methods for measuring an actual thermal resistance of building assemblies and mapping them into gbXML-based representations were also presented. The most recent studies in the IT-driven Building Automation System (BAS) for energy conservation purposes were also presented. Although their research addressed acquisition and automation of geometric building modeling and non-destructive thermal performance assessment processes from raw data including point clouds, images, and thermograpphs, it did not address extraction of material and textural information of building elements.

Ham *et al*. (2014a) and Ham *et al*. (2014b) presented a thermography-based method to calculate R-values of building assemblies and analyze condensation issues. The process visualizes thermal resistance and condensation problems in 3D while taking static occlusions into account. The result was a 3D visual representation of the actual thermal resistance distributions and building areas associated with condensation taking static occlusions into account by using 2D thermal images to reconstruct 3D spatio-thermal models to calculate the R-values. Wang *et al*. (2013) developed a hybrid system consists of a LIDAR and an IR camera to create a thermal 3D model of an existing building. The system linked point clouds acquired from a LIDAR with a thermal data at each point location, including temperature values.

Monitoring construction progress and safety is another focus area that is getting attention in the image processing field. Roh *et al*. (2011) used an object-based approach to monitoring detailed interior construction progress. They compared an as-planned 3D BIM with as-built photographs, in order to provide the user with a realistic perception into the interior construction process. Furthermore, Gao *et al*. (2014) and Yang *et al*. (2015) have used visualization platform to support different activities including corrective maintenance of HVAC, among others. In addition, automated reconstruction approach of mechanical systems in BIM, detection of structural components from CAD drawings for constructing as-is BIM objects and creation of 3D models from buildings' floor plans were investigated by several researchers (Cho *et al*. 2017, Cho *et al*. 2018, Lu and Lee 2017, Santos *et al*. 2011).

Integrating thermal information such as heat transfer, thermal performance, and thermal comfort level of an existing building with BIM are complex tasks due to the inaccessibility or lack of information available about the materials and their thickness (Natephra *et al*. 2017, Natephra *et al*. 2018, Abcdalla *et al*. 2014, Armesto *et al*. 2009). Lagela *et al*. (2013) used a GbXML schema along with visual recognition process as a standard output for the as-built BIM database, which was created from geometric and thermographic data. For the thermal characterization, a thermographic camera was used to capture IR images of the walls and roofs and then processed it as U-values. The U-values are coefficients of transmission of heat through the materials, which have become the standard for energy analysis. A thermally characterized as-built BIM was then formed, where the U-values provided descriptive information of the type of every building element. Ham *et al*. (2015) proposed a similar approach for updating thermal properties of building elements in the gbXML-based BIM through measuring actual heat transfer condition using 3D thermography. The outcome was an updated gbXML-based BIM, which was used as an input of the BIM-based energy analysis tools. Natephra *et al*. (2017) proposed a system that visualizes thermal information of building surfaces over time and evaluate the indoor thermal comfort condition in the building by integrating BIM with building surface temperature and air temperature (4D thermal information). The system uses sensors to implement thermographic survey to collect time–coded thermographic images. These acquired images are then integrated into BIM in order to visualize up–to–date thermal changes in the surfaces of a building's geometry. By considering the position of the occupant in the room, this method helps in calculating thermal comfort variables, such as operative and mean radiant temperature.

In addition to capturing of building information to generate as-Built BIM, several techniques have been used for detecting building deterioration prompted by material degradations, moisture invasions, or water leakages and their effect on energy inefficiency (Balaras *et al*. 1996). For example, thermal inspection was used for condition monitoring of laminates and others (Meola 2012, Kuenzer *et al*. 2013), Acoustic Pulse Reflectometry was used in leakage detection (Tafuri *et al*. 1997, Hunaidi *et al*. 2000) Leak Noise Correlators and Ground Penetrating Radar are used in leak detection (Maninder 2010), condition monitoring, Thermal IR was used in building auditing (Balaras *et al*. (1996), Balaras 2002) and quantitative IR thermography was used for building diagnosis (Grinzato *et al*. 1998).

2. Methodology, identification and integration of textual and material information

2.1 Methodology

As previously indicated, the purpose of this research is to develop a semi–automated methodology to identify the materials and textures of interior walls and integrate them with an as-built BIM. The proposed methodology for capturing material and texture data using IR consists of four stages as shown in Figure 1.

Stage 1: Image Capturing

A thermal IR camera is used to capture images of the target elements (walls, roofs, etc.) of an existing building. A Flir T640 camera has been chosen in this study. The camera needs to first be calibrated. The calibration begins with a complete operational check, verification of all internal cable and Printed Wiring Boards (PCB) connections, checking internal camera software, verification and/or re-equalizing as needed each temperature range for image uniformity.

Stage 2: Image Segmentation

The images captured in Stage 1 are then processed. If the target elements are interior walls (the case study), then only walls features will be extracted using a segmentation algorithm. Then, an image clustering process is used to categorize the similar regions of the target elements. The results of this process are different types of thermal contours representing the interior walls.

Stage 3: Material & Texture Identification and Extraction

The images are then transformed into emitted thermal infrared radiation and are also used to extract textural information. Statistical correlations between these values and models of target members such as interior wall materials made of gypsum and concrete of the test facility will then be obtained through a Gaussian Mixture Models (GMM) simulation approach and will further be used to extract material information from the images. Then Monte Carlo simulation will be applied to identify the materials and textures of the target elements. In this study, the target element used to test the proposed methodology were interior walls of an existing facility.

Stage 4: Population of As-Built BIM

The extracted texture and material information of the target elements is then integrated into the as-built BIM of the facility in a semi-automatic way, providing the data needed for multiple operations including facility management, preventive and corrective maintenance in addition to assessment of building conditions in relation to energy efficiency and water systems leaks. This sheet is then populated with the materials and texture properties and imported back to the BIM.

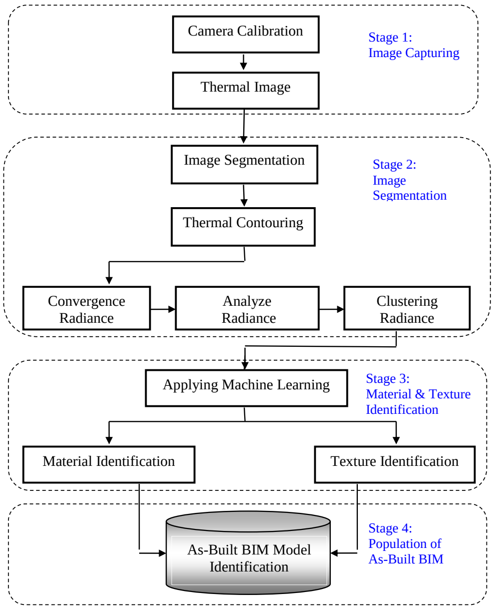


Fig. 1 Framework and workflow of the proposed method

2.2 Details of material identification

In order to identify the materials of target elements, (interior walls, in the case study), a prior process of material training must take place where interior walls with known materials will be used to define the types and then store it in the BIM material database. While each material has it is own thermal and reflectance property, unknown walls will then be imported for testing and verification in the database. For the material identification, the thermal images will be transformed into matrix of radiance values that represent each pixel in the image. The radiance values will then be analyzed to construct the different thermal distributions in the image that presents different material types. These radiance values will then be compiled based on their thermal properties that identify them as walls using the model (Machine Learning). Finally, when the model is ready, the process of identifying the unknown walls material becomes straight forward. Figure 2 illustrates walls material and texture identification workflow process.

2.3 Details of texture feature and identification

Texture feature is a visual characteristic that does not depend on color and intensity and reflects the intrinsic phenomenon of images. It is a combination of all basic surface properties. The texture may consist of some basic primitives and may also describe the structural arrangement of a region and the relationship of the surrounding regions. In general, the texture forms some interesting surface characteristics that can be derived from the image. The texture of an image is defined as the frequency of tonal variations in it. It is formed through the accumulation of component features, which can be too little to be detected separately from the image. Texture is a result of the elements pattern, size, shadow, shape, and tone in the image and it determines the overall visual smoothness

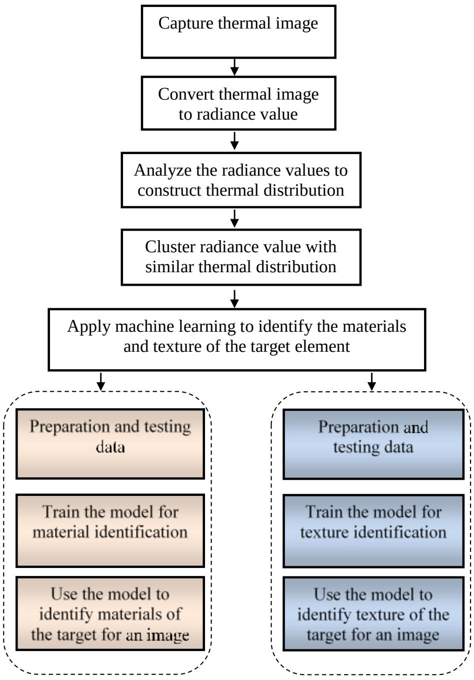
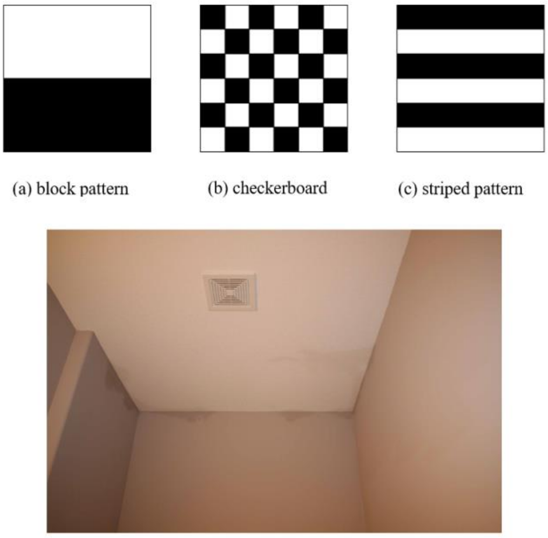


Fig. 2 Materials and texture identification workflow

or coarseness of the features in the image (Kiefer *et al*. 2008). Texture analysis helps to segment images into homogeneous areas of interest and represent these areas in a simple unique form. The texture of an image provides information about the spatial arrangement of the intensity values in the image, and as such contains information regarding contrast, homogeneity, rigidity, orderliness, etc. (Kottawar *et al*. 2014, Smith *et al*. 1996).

Figure 3 shows the color histogram for three different images that all have an equal number of white and black pixels. However, the texture of the three images is totally different although they have the same color histogram. The image shown in Figure 3 (a) is divided into two rectangles; a white and a black forming a block pattern, the image shown in Figure 3 (b) has eighteen black squares and eighteen white squares making a checkerboard pattern while the shown in Figure 3 (c) has three black rectangles and three white rectangles making a stripped pattern. Figure 3 (d) illustrates change of texture of the same material, which is gypsum board in this case, in the same image.

Texture identification performed within a single material type to identify the in-homogeneity within a surface. In-homogeneous surface may not be visible by the naked eye; however, the radiance values distribution can be used to identify the texture pattern throughout the image. For example, a wet wall might not be identified as such, initially. However it will have different radiance contours within it that can be analyzed differently to identify the changes in texture in the same material. In this study, a wall texture defines the homogeneity of the overall wall surface. In other words, if the clustering algorithm has more than one cluster, it indicates in- homogeneous surface. The method is similar to the material identification where machine learning is applied to define homogeneity of the wall surface. Figure 2 shows the walls texture and walls materials identification workflow.



(a) block pattern (b) checkerboard (c) striped pattern

(d) gypsum board ceiling and walls

Fig. 3 Three different textures and an image of a gypsum board ceiling and walls

2.4 Material and texture identification using Gaussian Mixture Models (GMM)

Identification of materials and textures can be considered as a classification problem in machine learning. Given a feature vector x the GMM approach models the probability distribution function (PDF) assuming a Gaussian distribution model. The assumption of having a Gaussian distribution of the underlying data is not random because of the characteristics of the heat diffusion in homogeneous materials.

Figure 4 presents the workflow of the process of materials and texture identification by performing a GMM to model the data and using maximizing log likelihood for parameters estimation. Based on our assumption of having a Gaussian distribution of the data, the prior distribution of the parameters estimates will be

$$p(\theta) = \sum_{i=1}^{k} \varphi_i N\left(\mu_i, \sum\nolimits_i \right)$$

where the ith vector is modeled by a Gaussian distribution with the parameters φ, μ and Σ. The estimation is based on prior given samples of data. Hence, p(θ) will be replaced by p(θ|x) in the above equation. Since the parameters of the Gaussian distribution (φ, μ, Σ) are unknown, the Expectation-Maximization (EM) algorithm can be used in an iterative way to estimate the distribution parameters.

Figure 5(a) shows the normalized radiance values patterns for different materials. Let λi be the model that corresponds to the material i. After the learning phase is completed (parameters estimation for each model λi) the model with the largest likelihood will be selected. Figure 5(b) shows the results of GMM analysis on a mixed data set of gypsum and glass materials.

The GMM approach is the general approach to the problem since it assumes mainly two things. First, the distributions of each material data is Gaussian and second those distributions can be split after knowing the parameters of each distribution.

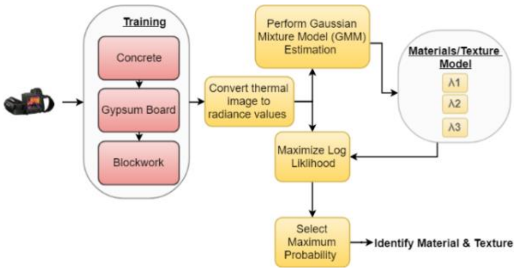
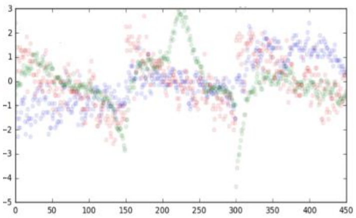
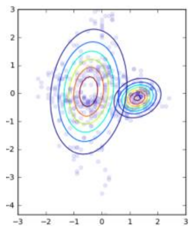


Fig. 4 Workflow for Material and Texture Identification using GMM model



(a) Normalized Radiance Values of Different Walls Materials



(b) GMM (Gypsum & Glass)

Fig. 5 Normalized Radiance Values of Different Walls Materials and GMM (Gypsum & Glass)

However, other method can be used in practice to enhance the GMM approach and differentiate the materials based on their probabilistic parameters. For example, using Monte Carlo simulation method to identify the μ, σ is a strongly recommended approach since the thermal images contains lots of samples and the Monte Carlo simulation tool is more practical and widely used in various software packages. In this study, GMM was first used and then Monte Carlo was applied to segment each image and identify materials of the interior walls of the test facility.

2.5 Case study: A hospital building

A multi-story reinforced concrete hospital building, located in Abu Dhabi, UAE is used for the case study. The Hospital building consists of a two-story basement including service accommodation, laboratories, central sterile services department (CSSD), dining and parking, and a three-story outpatient building. The building includes clinics, a link bridge, a three-story podium building that includes diagnostics units, operating theatres, ER unit, rehab unit, ICU and maternity units. It also includes two nine-story and two eleven-story inpatient towers, peripheral buildings including substations, cooling plant, workshop, mortuary, underground tanks and service tunnels. Data collected in this study include thermal images of the interior walls of the fourth floor of one of the towers of the test facility. Figure 6 shows the layout and a 3D view of the section of the fourth floor in which the experiment of this case study was carried out.

Autodesk Revit software, that allows the users to design a 3D model of the building components, was used to create the BIM of the test facility. The Revit feature, that provides 2D annotations and extraction of building information and quantities from the model's integrated database, was employed. The level of development (LOD) of the BIM of the test facility is 400, which includes accurate quantities, shapes, sizes, locations, and orientations of the structural elements. The full integrated model consists of architectural model, structural model, interior

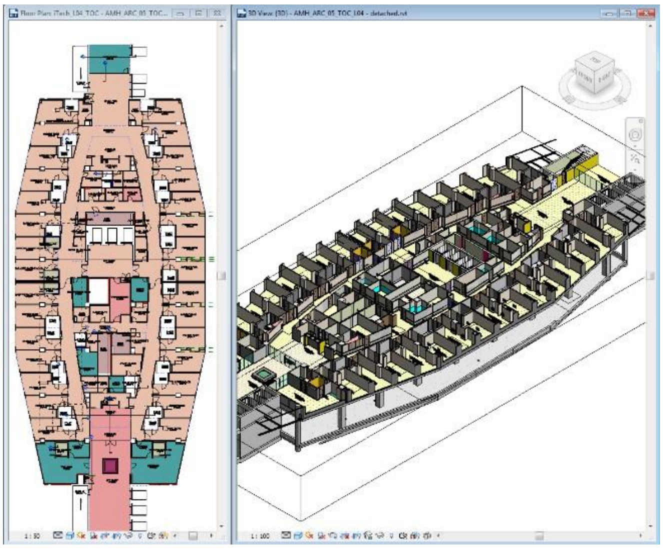


Fig. 6 Layout and 3D view of section of fourth floor of Tower C

model, Mechanical, Electrical, Plumbing (MEP) model, and Facade model. However, the only models used in this project were the architectural, the structural, and the facade models.

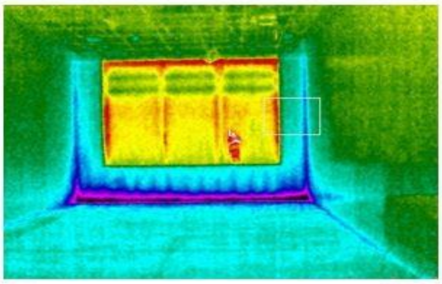
The defined methodology and framework with its four stages was followed in carrying out this case study stage by stage.

Stage 1: Image capturing of the target walls

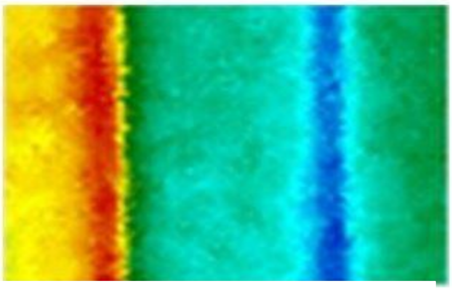
In this stage of image capturing, a FLIR T640 Infrared camera was used to collect thermal imagery of the internal walls of the Hospital building. Prior to data acquisition, the FLIR T640 camera was calibrated by the vendor. This procedure was established using a calibration field consisting of a black wooden plate with aluminum targets distributed, identifiable due to their different emissivity values with respect to the background. The spatial distribution of the aluminum targets is mainly required for the accurate determination of the camera focal length (Kuenzer *et al*. 2013). Data acquisition was performed in the afternoon at a temperature of 25^{o} C and relative humidity of 58%. Images were acquired for the targeted internal walls in the rooms of the fourth floor of the target tower, and some of the basement (parking) area walls. The process took order in terms of the element ID that were generated for each wall in the BIM and then manually assigned to each image and excel file accordingly. The material of the imaged walls consisted mainly of interior gypsum board in the inpatient rooms and concrete and block work in the other areas. The IR images were then processed using the techniques described in the following stages in order to extract material and texture information of the walls and further integrate that into the BIM of the hospital.

Stage 2: Image segmentation and exploration of the target walls

Once all of the thermal infrared images were acquired, texture and material information were extracted by texture referencing of thermal information at each pixel in the images. The main objective of the data processing phase of the project was to extract thermal information from the images and further transform it into understandable form that defines the texture and the material of the interior walls.



(a) Original 640 x 480 pixel



(b) Enlargement showing 100x100 pixel

(c) Enlargement 10x10 pixels

24.52	24.57	24.63	24.54	24.65	24.56	24.56	24.56	24.54	24.52
24.58	24.64	24.63	24.6	24.59	24.56	24.56	24.53	24.56	24.56
24.56	24.61	24.62	24.61	24.63	24.56	24.53	24.54	24.54	24.58
24.63	24.56	24.69	24.58	24.61	24.61	24.58	24.56	24.55	24.54
24.6	24.62	24.65	24.64	24.61	24.62	24.58	24.59	24.56	24.61
24.69	24.67	24.63	24.6	24.59	24.58	24.62	24.58	24.61	24.57
24.63	24.67	24.65	24.65	24.59	24.61	24.65	24.7	24.6	24.61
24.61	24.63	24.65	24.69	24.69	24.57	24.61	24.6	24.59	24.58
24.63	24.67	24.71	24.69	24.67	24.65	24.66	24.66	24.68	24.6
24.64	24.68	24.68	24.61	24.57	24.59	24.59	24.61	24.59	24.66

(d) Part of the image attribute table showing temperature values at each pixel

Fig. 7 Basic information of the thermal IR image

After acquiring the images, a feature extraction process was carried out in order to keep only the images of the interior walls. Although it is recommended to take the image of a wall with the camera directly facing it; with horizontal camera axis and clear line of sight, images taken with slightly different orientation can still be geometrically corrected using the software that comes with the camera (FLIR Quick Report v1.2). The images acquired in this project were taken with an average length of the line of sight of 2 meters, and were first processed using FLIR Quick Report v1.2 software for feature extraction and basic image processing. The outcome of this process was raster models of the emitted thermal infrared radiation, which were first converted into temperature at each pixel. Figure 7 shows a sample thermal image of the test facility (also known as thermographic image) and the basic information it contains. Figure 7(a) shows the original 640 x 480 pixel image, Figure 7(b) shows the enlargement with 100x100 pixel image Figure 7(c) shows the enlargement with 10x10 pixels image and Figure 7(d) shows part of the image attribute table with temperature values at each pixel. Then, an algorithm for texture segmentation *was* developed in this study and applied to automatically extract textural information needed for identification of the materials of the walls. This texture segmentation algorithm splits the image into different homogeneous texture regions. Figure 8 displays the result of texture extraction and feature labeling of an interior gypsum board wall and window in a thermal image. Figure 8(a) showing the original digital image, Figure 8(b) shows the corresponding thermal image while Figures 8(c), 8(d) and 8(e) show wall features isolated from the rest. The outcome of this process was raster models that represent the emitted thermal infrared radiation in the thermal image of the interior wall material, since only interior walls were considered in this study, interior gypsum board and concrete have been identified and used as the two common material types of the interior walls.

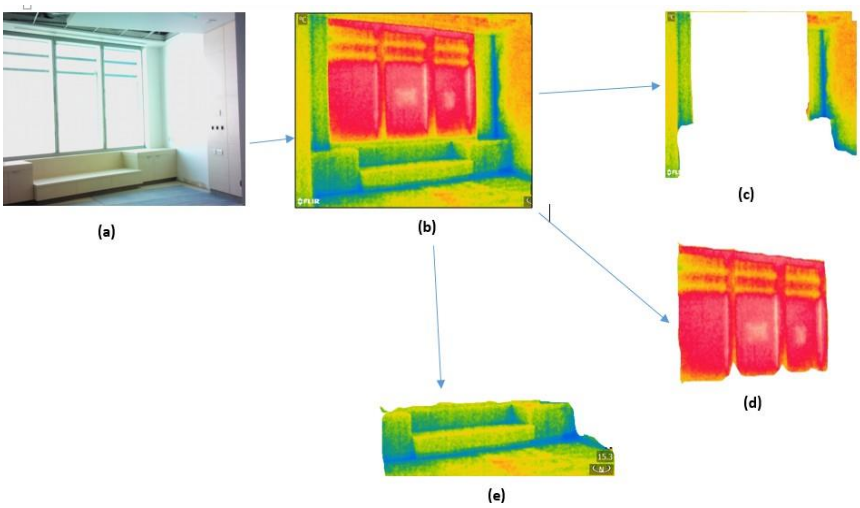


Fig. 8 Texture extraction and feature labeling of an interior gypsum board wall and window in a thermal image

Stage 3: Material and Texture Identification and Extraction

Here, the outcome of the previous stage was analyzed in order to identify the materials of the imaged walls and extract material and texture information. The objective of this part of the methodology is to search the outcome of the previous process for a pattern that can help in identifying the material of the imaged walls. Since each thermal image is represented by a grid (i.e., matrix) of pixels that stores emitted thermal infrared radiation values at each pixel in the images of the interior walls, these values can be represented by a random variable. The statistical properties and distribution of this variable were analyzed for correlation with the type of material of the imaged walls. Such problem is a general classification problem in the field of data mining (Kottawar *et al*. 2014). A common approach for estimating the statistical characteristics of such a variable is the Monte Carlo Simulation (Robinstein *et al*. 2008). Monte Carlo Simulation is a modeling and simulating technique that generates several scenarios and gathers relevant statistics in order to assess relationship between the variable in question and a model of interest. The emitted thermal radiation matrices generated in the previous processing phase exhibit random behavior that make Monte Carlo Simulation a suitable approach that can help in segmenting each image and further identifying the materials of the interior walls.

Monte Carlo Simulation was utilized given the relationship between the mean and the standard deviation of the emitted radiance matrices of each image and the mean and variance of a model of two material types adopted in this study as target materials, which were interior gypsum board and concrete.

After identification of texture and material information of the interior walls, extraction these information has been carried out. The outcomes of this process were the textural and materials information of the interior walls identified based on the statistical characteristics and the models of gypsum board and concrete. The processed images have been transformed into data that represent the texture and the material of the imaged walls, and this information was then exported into MS Excel and sorted according to each walls unique identifier in the BIM database in preparation for texture and material integration into the as-built BIM database.

Stage 4: Population of As-Built BIM

The way in which texture and material information were integrated into the BIM database of the test facility is described in this section. In the as-built BIM database of the test facility, two new project parameters were created for the interior walls, which are “Surface Texture” and “Surface Material”. Since the Revit software doesn’t define the texture of the target elements in the BIM, the type of new parameter defined in this case was “Text”, which was grouped under “Energy Analysis” category. This means the texture of the interior walls was described in text format in the BIM database. On the other hand, and since Revit has a built-in material library, the new parameter for material was defined as “Material”, grouped under Materials and Finishes, and was mapped to the existing material library in the BIM database.

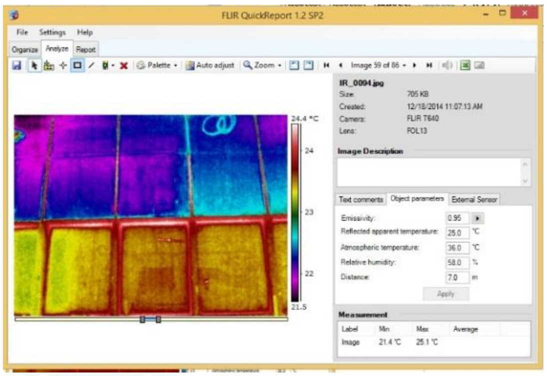
A schedule of the interior walls was then created using Autodesk Revit in the test facility BIM, which included the following parameters: Elements ID, Family Name, Area, Length, Volume, Surface Text, and Surface Material. Then, the wall schedule was exported into MS Excel using a tool called Ideate BIMLink, which is a freely available third-party tool that can be installed and integrated in the Autodesk Revit software. This tool allows users to extract data from a Revit file into Microsoft Excel and further to export the up- dated database file back into Revit in a user-friendly fashion. This tool was used in order to automate and speed up the process of populating the values of the newly extracted textural and material information of the interior walls into the BIM of the test facility.

3. Results and discussion

3.1 Image segmentation and exploration results

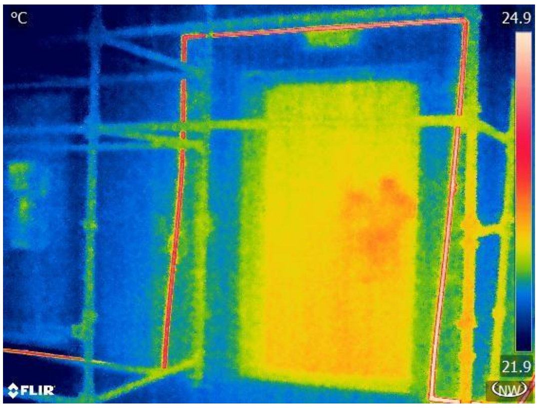
After acquiring the images, the first step was to enter all the images into the FLIR QuickReport software for pre-processing, which included geometric corrections of images taken with the line of sight slightly off the horizontal. Using FLIR QuickReport software tools, emitted thermal IR images of the walls were then converted into temperature values, and exported into MS Excel. The emitted thermal infrared radiance, emissivity, ambient temperature, atmospheric temperature, relative humidity, and line of sight distance were also provided as outcomes of the process. Figure 9(a) shows a thermal image of one of the interior walls (Blue) and a window (Yellow) collected in this project as displayed in the FLIR QuickReport software. It is common in thermal analysis that different palettes or colors are explored depending on the type of study and user interest.

The FLIR QuickReport software provided an Excel sheet for every image processed for the interior walls storing the emitted thermal infrared radiance values of the corresponding pixel, which are convertible to temperature values. In this study, this information was used to identify the material type of the interior walls. Since the focus of the case study was the interior walls of the test facility, all non-walls data was not needed. An algorithm was created in Python and used to filter out all non-walls parts of the images. Two main libraries were imported and used in this Python in order to perform this filtering process including the Python Image Library (PIL), which contains image import and filtering functions and Skimage (also known as scikit image), which contains a collection of numerical algorithms used to process the images. Once an image is imported, the matrix is converted into an array where the image analysis takes place. Then, in the image analysis phase, the algorithm tries to find similar contours and common features in the image, identifies it, and plots the results. Below is an example where the algorithm identified and

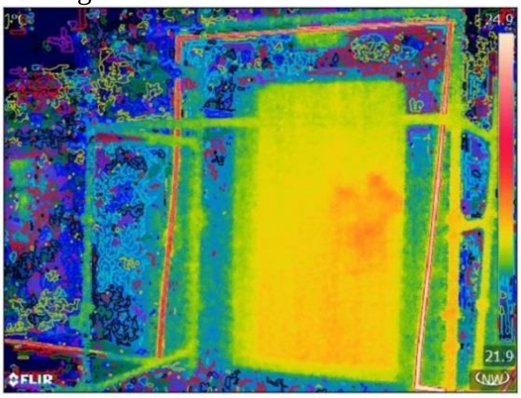


(a) FLIR QuickReport window

(b) Digital image of concrete wall with door and scaffolding



(c) Thermal image of the thermal image of



(d) Thermal image after applying the filtering algorithm of Python

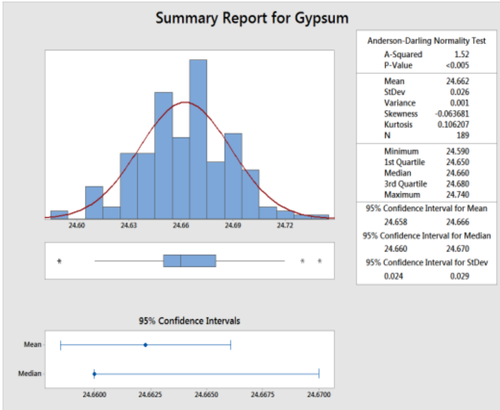
Fig. 9 FLIR QuickReport window capture and digital and thermal image of concrete wall with door and scaffolding

further selected an interior wall from the rest of image components (Figure 9(b), (c), (d)). Figure 9(b) shows a digital image of a concrete wall with a door opening and some steel scaffolding and an electric cable above the door. Figure 9(c) shows the corresponding thermal image where the steel scaffolding were shown in the image using color tones similar to that of the wall, while the door opening was shown in yellow and the electric cable was in red color. This image was filtered using the algorithm described above in order to extract only the wall (Figure 9(d)). Note that in the filtered image shown in Figure 9(d), the door opening, the steel scaffolding, and the electric cable were filtered out.

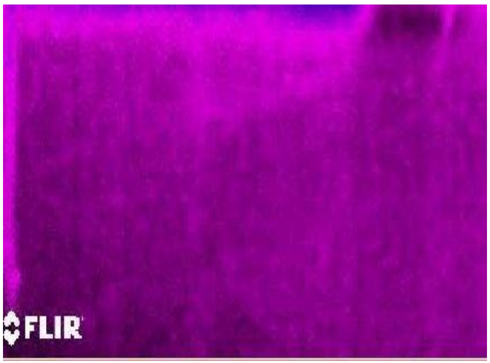
3.2 Identification, extraction and population of texture and material information into the BIM

Monte Carlo Simulation was used to find the correlation between the emitted radiance data of the images *and* the models of interior gypsum board and concrete in order to identify the material types in the interior walls images. The main purpose of using the Monte Carlo simulation was to analyze trends of the emitted radiance recorded in each image such that these values are

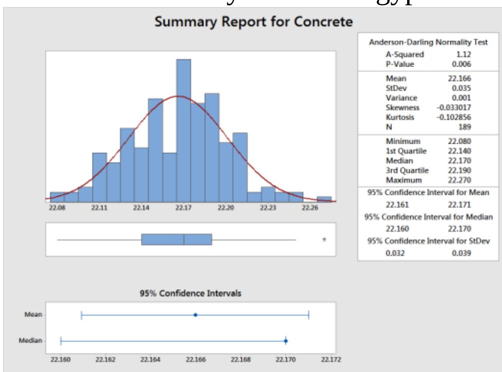
(a) Interior gypsum board thermal image



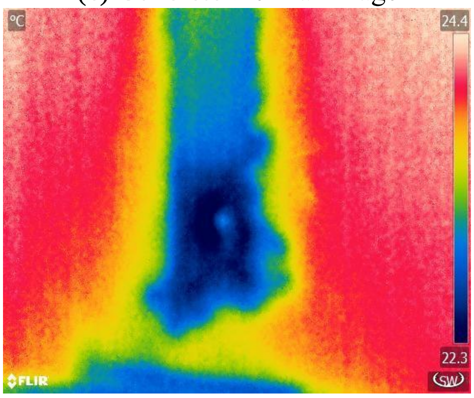
(b) Statistical summary of Interior gypsum board



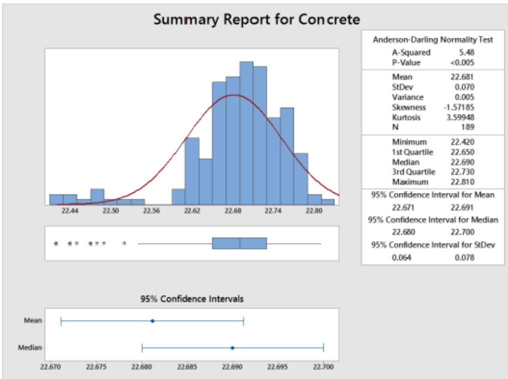
(c) Concrete thermal image



(d) Statistical summary of the concrete



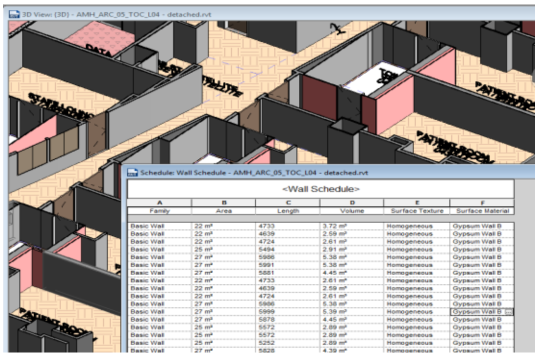
(e) Cracked concrete thermal image



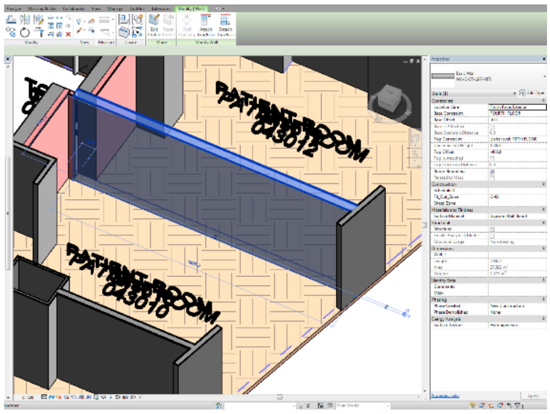
(f) Statistical summary of the cracked concrete

Fig. 10 Thermal images and corresponding statistical summary

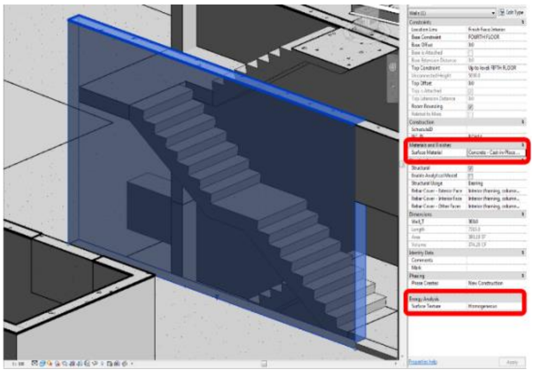
represented by the probability distribution instead of by single emitted radiance values. The results of the Monte Carlo simulation are distributions of possible outcomes rather than the one predicted outcome that a typical deterministic model would provide. That is, the range of possible defined material types that could be identified and the likelihood of any outcome occurring based on the mean (μ) and standard deviation (σ) of the distribution. In order to produce models of interior



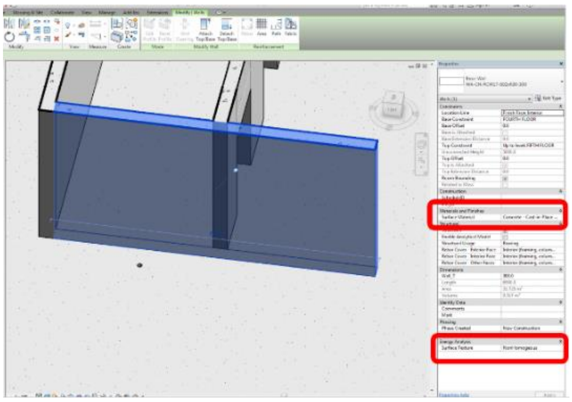
(a) Gypsum Wall Board schedule in the BIM



(b) Updated BIM showing Gypsum Wall Board material and homogeneous texture of the interior walls



(c) Updated BIM showing concrete surface material and homogeneous texture of the interior walls



(d) The updated BIM showing concrete surface material and inhomogeneous texture of the interior walls

Fig. 11 Gypsum wall board and concrete surface with homogeneous and nonhomogeneous textures

gypsum and concrete, ten samples from each of the two material types were used in the simulation process. Figure 10 shows examples of thermal infrared images of the two material types used in this study; interior gypsum board and concrete walls, along with the summary of their corresponding statistical characteristics.

After the texture and materials information of the interior walls were identified and extracted, they had been used to populate the newly created parameters. Once the database was updated with the texture and material information (Figures 11(a) and Figure 11(b)), it was exported to Revit using Ideate BIMLink tool. In the Revit-based BIM, the interior walls now have two new parameters populated with texture and the material information (Figures 11(c)). Similar to the integration of the gypsum board above, the same procedure was applied for the concrete walls. However, notice that here there was an inhomogeneous texture wall that was identified and reflected in the schedule of the Revit database as well as in the BIM as shown in Figures 11(d).

4. Summary and conclusions

As-Built drawings are expected to represent the building conditions accurately in order to allow facility managers and energy auditors to perform correct analysis and communicate the as-is building conditions to the owners in a better way. To achieve this goal, this paper presented a semi-automated method for extracting material and texture information of the interior walls using infrared remote sensing and integrating the extracted information into the as Built-BIM of a test facility. Such an updated, as-built BIM, would allow practitioners to accurately identify potential problems given the homogeneity of the texture and/or material of a wall. As a proof of concept, a hospital building (test facility) was used as a case-study. Thermal and digital images of interior walls were acquired for the interior walls of the test facility using a consumer-level single thermal IR camera. The resulted thermal images of the interior walls were then converted into emitted thermal infrared radiance. A statistical analysis approach of the emitted radiance distribution based on Monte Carlo simulation was used in order to identify interior walls surface texture and materials (interior gypsum board and concrete). Surface texture and material information were extracted and then integrated into the database of the as Built-BIM of the hospital. With this information integrated into the BIM, one can identify inhomogeneous textured wall patterns and further identify potential problems such as heat loss or water leakage. The method developed in this study will help energy auditors in saving the time normally spent in analyzing large numbers of thermal images provided by site technicians, and instead focus on the sources of the problems and examine various retrofit alternatives.

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