INTEGRATION OF TEXTURAL AND MATERIAL INFORMATION INTO BIM USING SPECTROMETRY AND INFRARED SENSING

by

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Dedication

To my inspiring parents,
sisters and brother,

for keeping their prayers and hope alive,
for their love, endless support and encouragement.

Abstract

As-built data and drawings are essential documents that contain object dimensions, locations, materials, and other important information used by different parties during the processes of the building design, construction, and operation in order to perform commissioning or energy analysis, and preventive and corrective maintenance. These documents go through many changes and updates throughout the construction phase and after the handover, and this process is currently tracked manually which is time consuming. In the Architecture, Engineering, and Construction (AEC) industry, Building Information Modeling is increasingly used throughout a facility's life cycle for various applications, such as planning, conceptual design, detailing, fabrication, renovations, space usage planning, and managing building maintenance. For existing buildings, as-built Building Information Models (BIMs) are often constructed using dense, three dimensional (3D) point clouds data obtained from laser scanners. Laser scanners can quickly detect and capture the “as-is” conditions of a structure, and then the points get processed to obtain the 3D geometric model. Traditionally, as-built BIMs do not have material and textural information of the buildings integrated into them. This thesis presents a methodology for generation of textural and material rich as-built BIM Models. The proposed method used thermal infrared sensing to capture thermal images of the interior walls of an existing building. These images were then processed and only walls’ features were extracted using a segmentation algorithm. The digital numbers of resulted images were then transformed into radiance values that represent the emitted thermal infrared radiation recorded at each pixel of the interior walls images. These radiance values were used to extract textural information from the images. Statistical correlations between these values and models of interior gypsum and concrete were obtained through a Monte Carlo simulation approach and further used to extract material information from the images. The extracted texture and material information were then integrated in the BIM Model, providing the data needed for the assessment of building conditions in relation to energy efficiency and water and waste water systems leaks.

Search Terms: As-Built BIM; Building Materials; Thermal imaging; Thermography; Texture Extraction.

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Chapter 1: Introduction

1.1 Overview

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 actual construction, are [1]. In order to track and control the construction process, most project managers focus on gathering accurate, complete, quick, and reliable field data for ongoing construction projects, which includes material and equipment tracking, progress monitoring, and quality assurance. Nonetheless, 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 [2], [3].

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 [4]. Today, full documentation of information faces many difficulties and challenges [1], [2], [3], [5], [6]. Information about a specific element that exists in reality might not be recorded or changed without being verified. Otherwise, the quality might drop without being noted, and these undocumented changes normally lead to unnecessary efforts and costs [4]. A study by the National Institute of Standard and Technology (NIST) found out that the cost of inadequate interoperability of building information experiences was about $6.12 per square foot for new construction and $0.23 per square foot for maintenance [7]. Moreover, more than $1.5 billion are lost every year in the United States due to the lack of information at construction sites for the maintenance and repair personnel [5]. Currently, documentation procedures are mainly done manually, which is extensively time consuming, labor intensive, error-prone, and costly [3], [8]. Current methods for data acquisition at construction sites include laser distance meters, digital cameras, measuring tapes [9], and laser scanners [3].

There is a demand to automate the data acquisition and storing processes in order to support facility personnel in getting all necessary information about the building whenever needed [2]. 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. [1], [2], [3].

The use of technology in data collection has many advantages in improving the process by reducing the acquisition time [2]. Such technologies include smart tags, Radio Frequency Identification (RFID), infrared sensors or cameras, laser scanners [2], and terrestrial photogrammetric techniques [9]. Infrared cameras and photogrammetric techniques are a form of remote sensing, which is the science and art of capturing information about objects, areas, or a phenomenon through the analysis of data acquired by devices that are not in physical contact with the object, area or the phenomenon [10], [11]. However, after successfully collecting the necessary information of the existing building, there should be an efficient way to integrate and store the collected data and easily access it. Current methods of storing the collected site data include paper documents (rolls of drawings from the architect and engineers, folders of equipment information for each type of equipment, file folders of maintenance records, etc.) [12]. Other relatively advanced methods include hard copy and digital photographs, two-dimensional (2D) and three-dimensional (3D) CAD files, and Building Information Models.

Building Information Model (BIM) is a term that has become very common in the design and construction fields over the past 20 years [13]. BIM transformed building information documentation from paper-centric processes into a digital work-flow 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 product industry wide [7]. 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 created or gathered about that facility in a format useable by all throughout its lifecycle” [14].

BIM provides a new approach to represent the information required for the design, construction, operation of constructed facilities, and rehabilitation. A BIM can also be used to integrate scheduling and cost estimating as a fourth (4D) and a fifth dimension (5D), respectively. The information model can include contract and specification properties, personnel, programming, quantities, cost, spaces and geometry [7], whereas 3D CAD modeling was merely collections of points, lines, 2D shapes and 3D volumes. In BIM, such geometric entities can also have a symbolic or abstract “meaning”, as well as quantitative or qualitative information [7]. Figure 1 shows an example of a BIM of a multi-storey building displayed in Autodesk Revit BIM software with its information shown in the different windows in the same interface.

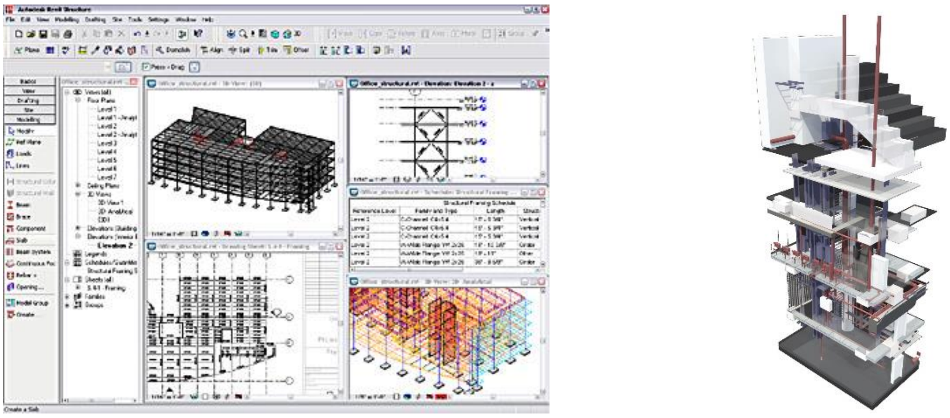


Figure 1: An example of a BIM model of a building [15]

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 building’s life cycle including rehabilitation. The information collected with a nondestructive, automated process such as remote sensing, stored in a BIM-compliant database 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 [1]. Spectral properties of object surfaces (e.g. 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, wavelength of EMR, texture, and the illumination angle (angle between the inward surface normal and the direction of EMR). Remote sensors capture the amount of reflected, absorbed, transmitted, or emitted radiation and record that in a form of digital numbers at the location of every pixel in the image. Digital numbers represent the average radiance recorded at the location of each pixel and they are also referred to as brightness values [10].

Previous research reported in the literature mainly focused on extracting the geometric properties of the existing buildings [5], [11], [16] using remote sensing techniques such as laser scanners or photogrammetric techniques [9], [16], [17] for as-built data, but without automatically or semi-automatically extracting the attribute information of building elements. Examples of attribute information of building elements include material, texture, water and energy losses, heat dissipation, structural defects, cracks, etc. There is a need in the construction industry for an automatic or semi-automatic method for extracting such essential information. In this study, a framework was developed to extract and integrate extracted textural and material information into a BIM model of test facility using an infrared remote sensing technique.

Infrared (IR) sensing is a form of remote sensing that employs electromagnetic radiations (EMR) between the visible and microwave radiations in the wavelength range from 700 nanometer at the edge of the red to about 1 mm [10]. This portion of the EMR spectra is commonly partitioned into near-, mid-, and far-infrared portions (Figure 2).

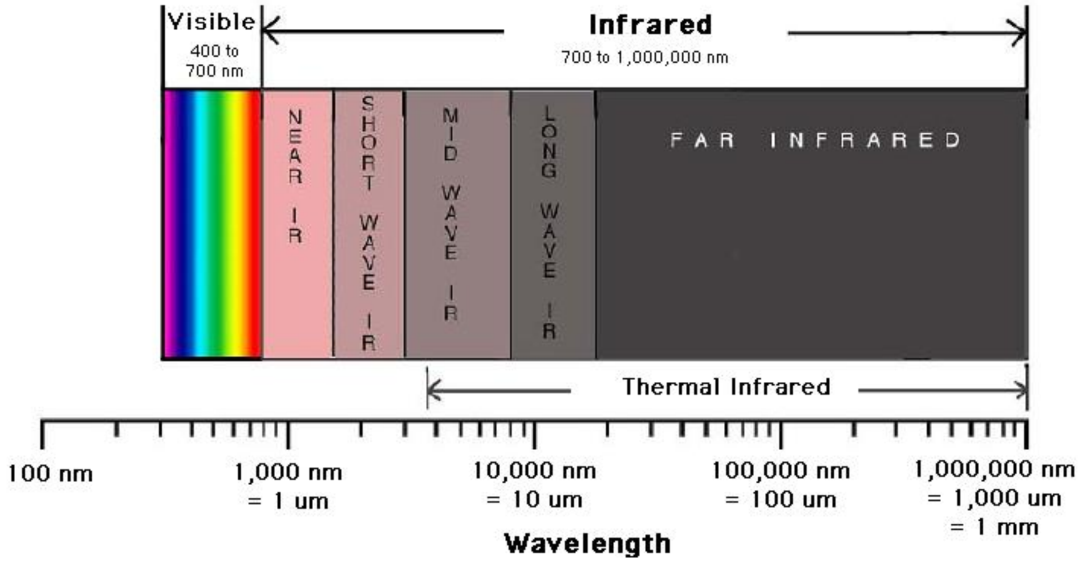


Figure 2: Infrared spectrum

Thermal infrared radiation (3.0μm – 15μm) is emitted by objects. It can be recorded by thermal sensors (e.g. thermographic cameras) as radiance, which can be converted in surface temperature. The amount of emitted energy of the thermal IR depends on the temperature of the surface of the object although normally much of the emitted energy is absorbed by the atmosphere. An IR sensor (e.g. IR camera) typically records EMR at specific locations within the wavelength range stated above. For example, a thermal IR camera such as the one utilized in this study, operates generally at wavelength greater than 900 nanometer and produces thermal images (also known as thermographs) that can be used to detect thermal isolation and heat dissipation in buildings. Such an IR camera has many advantages that can be utilized in the construction industry such as [18]:

1. It is contactless, therefore nondestructive and reactionless.
2. It can be used to measure objects in very hot and difficult-to-access areas.
3. It allows for rapid data acquisition.
4. It measures the temperature of a solid-state body surface, not the surrounding atmosphere.

Over the past decades, successful applications of thermal infrared imaging have been made in many fields such as locating geologic faults, soil mapping measurement of soil moisture, locating water leaks, locating cold water springs, detecting faulty heat equipment, etc [10]. This involves partitioning of the thermal infrared image into different segments that have similar spectral characteristics. Since images can have different features and contents, effective processing and retrieving of an image from a large image database can be very challenging. A main form of image processing is image classification, which means segmenting the image into homogeneous zones and labeling the resulted zones with distinct class labels. While this is an easy task for humans, it has proved to be a difficult problem for machines and computer software [10], [19], [20], [21]. Over the past years, researchers from different fields such as, computer graphics and vision, machine learning, information retrieval, human-computer interaction, database systems, data mining, information theory, statistics, and psychology researched many methods for image interpretation using a wide variety of concepts. One well-known one is known as Content-Based Image Retrieval (CBIR), which uses the visual content of a digital image to help organize its contents. The term "content" in this context mainly refers to color, shape, texture, or any other useful information that can be extracted from the image.

In this project, the texture forms an interesting content of the image that will be useful for different applications. The texture of an image is defined as the frequency of tonal variations in it. It is formed through 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” or “coarseness” of the features in the image [10]. 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 [22], [23]. In Figure 3, the color histogram for the three images shows that it has equal number of white and black pixels. However, the texture for the three images is totally different although they have the same color histogram. The left image in Figure 3 is divided into two rectangles; one white and one black forming a block pattern. The center image has eighteen black squares and eighteen white squares making a checkerboard pattern. The right image has three black rectangles and three white rectangles making a stripped pattern.

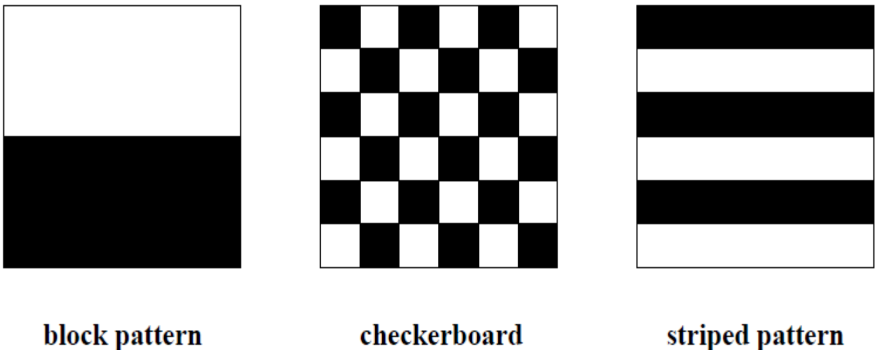


Figure 3: Three different textures with the same black and white distribution [24].

In this study, a thermal infrared camera was used to obtain thermal images for the interior walls of an existing building. These images were processed and analyzed to extract the texture of the imaged walls, which was used to assess the homogeneity of each wall. Then, an algorithm was applied for automatic identification of the material of the walls. The material and textural information of the interior walls has then been integrated into the BIM model of the test facility and used in detecting thermal and heat losses from the building, applying energy and sustainability analysis, as well as water and waste water leaks detection.

1.2 Problem Statement

Due to contractor errors, poor documentation, or on-site problems during the construction phase, the documents of a building often vary from how they were originally designed by the architects, Issued for Construction (IFC) drawings, shop drawings, and even after the project handling. Therefore, the value of this information drops quickly, for the reason that it is typically not updated to reflect finished conditions of the facility or in a form that is easily accessible and convenient. Moreover, verification of the real and most updated data using the traditional processes usually results in incorrect or incomplete records. To enable accurate engineering analysis, as-built models must be produced to efficiently represent the building in its real updated form. Today, research efforts are being carried out to address the automation of updating the as-built data of an existing facility. Of the main focus of this research is on extracting textural and material information of the interior walls of the test facility using infrared sensing techniques and further integrating that information into the BIM of the facility. However, facilities can be complex environment while geometric information is insufficient for assessment. Until now, limited research has been carried out on the recognition of Building Information Model (BIM) specific components such as walls. A method of the integration of the material and texture information of an existing building with the 3D geometric data (BIM of the facility) was developed. Certainly, a BIM database populated with textural and material information would provide an automatic framework for detection of heat losses and water and waste water system leaks.

1.3 Objectives

The main objective of this study is to develop a methodology for extracting textural and material information of an existing building using an infrared sensing and further integrating that into the BIM. This proposed method will enhance the current procedures by enriching the BIM model of an existing building with useful information that will aid in energy analysis and water and waste water systems leaks detection.

The detailed objectives are:

1) Extract material and textural information of an existing building using a thermal infrared camera.
2) Develop a framework for representing, organizing, and integrating the acquired material and textural data into the BIM.
3) Perform basic analysis on the rich BIM after integrating the new information to explore the advantages and limitations of the study for the industry.

1.4 Significance of the Project

Having a full record of information of a facility is essential as it supports the owners and building energy auditors in assessing building performance, managing building repairs, and renovations. However, full documentation of information of an existing building faces many difficulties and challenges. Information about a specific building object that exists in reality might not be recorded during construction or it might change. This change is not verified, which will lead to unnecessary efforts, which can be costly and time consuming. Previous research have addressed issues related to utilizing remote sensing technologies such as laser scanners to collect geometric information about an existing facility and transforming that into the geometric component of a BIM model. This method proofed to provide an accurate geometric database that would help in facility maintenance and space management. However, having a geometric-rich BIM model is not enough to determine the condition of the facility as there are many other important parameters that cannot be obtained by laser scanning such as textural and material information. The aim of this research was to extract material and textural information using infrared remote sensing integrate that into the as-built BIM model of a test facility. This would help in creating an updated information-rich BIM database, which would be useful in energy analysis and detection of defects in the elements of the building/facility such as water and waste water system leaks.

1.5 Thesis Organization

The rest of the thesis is organized as follows: Chapter 2 provides a review of the state-of-art in remote sensing, building diagnosis, thermal imaging, texture extraction, and building information modeling (BIM). Chapter 3 presents the methodology developed in this project for extracting textural and material information from imagery taken for the interior walls of the test facility through infrared remote sensing. Chapter 4 presents the results obtained after applying the methods developed in this study. Chapter 5 presents the conclusions and the findings of this study and provides some recommendations for future research.

Chapter 2: Literature Review

The objective of any owner in the construction industry is to save time and money, while maintaining quality and safety. Therefore, there is always a need for research efforts and experiments in order to find the best solution to best serve the industry. Technology is one of the successful factors for implementing successful experiments. It helped many industries throughout the history. Through technologies, project parties and teams take advantages of faster communications, smaller and powerful computers and devices, and rich digital tools [25]. Utilizing remote sensing tools to extract buildings information and combining them all in one integrated model is one of the exciting research activities at the moment. Until now, literature states no standard procedure to utilize such methods. This chapter provides a review of the literature on this topic as it relates to remote sensing, texture and material information of buildings, BIM, and current techniques of BIM creation from laser scanning.

2.1 Remote Sensing for As-is Building Information Extraction

Remote sensing technology is not new in construction industry and has been utilized in different ways [17]. Barcodes, for example, were used to extract location information about specific objects in the construction site. Barcodes have been used all over the world as the product identification method of products and manufacturing equipment [26]. Another sensing technology; LADAR (Laser Detection And Ranging) has also been investigated for reading barcodes at a distance of about 50m in the site. LADAR are active remote sensing systems that use pulses of laser light instead of radio waves, and the return time for each pulse is analyzed to calculate distances between the locations of the sensor and the object of interest [10]. The concept lies in the high intensity image produced form the LADAR values that are captured from the highly reflective materials. The major benefit of this method is that there is no need for additional hardware to obtain the requested information. However, this method has some limitations as it is applicable only for short distances, requires huge amount of manpower, and ineffective in harsh environment due to defects or dirtiness of the barcode which makes it hard for the LADAR to read [2].

Similar to barcodes, Radio Frequency Identification (RFID) and Wireless Local Area Network (WLAN) technologies are also being used in construction for project control to replace manual processes such as tracking and locating materials and other assets [2]. RFID tags have a unique identification number that is used for resource identification where they respond to radio frequency waves [2]. Furthermore, this method presents a number of advantages over barcoding as it does not require clear line-of-sight and clean environments since these tags are excited by radio waves and that the stored data can be modified anytime [27]. RFID are currently being researched for indoor localization, as they can assist facility management with their fast automated benefits. One of the researched applications of using RFID technology is to identify and store maintenance history information about fire hose reels and valves, and therefore access the information whenever needed by workers or inspectors [28]. The RIFD were tagged to hose reels and valves in fixed locations and the values were obtained using Ultra High Frequencies (UHF) RFID. Results showed that the UHF RFID perform well with metallic objects even with the presence of obstacles.

The previously mentioned methods use tags that are assigned to objects in the building during or after the construction, which means someone has to actually go to the location and tag the objects with the right information and then use the reader to extract the information. However, this is not always the case as some old buildings do not have tags or any recorded documents about their geometry or materials. Three-dimensional (3D) imaging technologies such as laser scanners are capable of capturing detailed information about the geometry, and sometimes textural information of visible surfaces of structures, and are capable of analyzing them using active sensors in short period of time, without the use of any type of tags. Laser scanners emit vertical and horizontal laser signals from their rotating photon source to measure distances from the source to the objects and to acquire dense range data. The rotation of the photon source permits a "scan" of the surrounding environment and generates a spherical coordinates of dense set of 3D points of the scanned objects [29]. Recently, research has explored the use of laser scanners as an alternative to traditional surveying methods for the construction of as-built models for different purposes. Advantages of laser scanners over other remote sensing methods include: high measurement density and accuracy, fast data acquisition, and canopy penetration. The collection of dense set of points makes it possible for detailed modeling of complex building elements as well as 3D documentation of as-is conditions, which can help in supporting decisions about facility operation, maintenance, rehabilitation and energy analysis [17]. Figure 4 shows a digital image of Whitney Toll Bridge (left) and the corresponding point clouds produced by Leica laser scanner.

Figure 4: Left: Whitney Toll Bridge, Right: Whitney Toll Bridge laser scanned point clouds [30]

Another remote sensing method; photogrammetry is used to obtain spatial measurements and other geometrically reliable derived products from photographs [10]. Photogrammetric procedures vary from obtaining approximate distances, areas, and elevations using hardcopy photographs captured using unsophisticated equipment to generating digital elevation models (DEM), orthophotographs, GIS data, and other digital products using sophisticated techniques. Photogrammetry has been widely used in engineering laboratories for testing materials [31]. The process works by placing specific targets well on objects to be photographed and then identifying the coordinates of the targets. Numerous photos of each object are then taken from different positions and angles. Then the texture and color data can be extracted, related to the captured objects. Laser scanning and photogrammetry have been integrated in a recent research study in support of progress reporting and documentation of as-built information in the construction industry [32]. The results provided needed information on quantities, material type and texture of the scanned object. As an example, unpainted objects are hardly identified using the scans obtained from the laser scanners only, and thus a photo image can be acquired and used to identify these objects. On the other hand, using photogrammetry alone is not useful to identify quantities, material types, and texture.

2.2 As-Built BIM Models

Research has shown that BIM for existing buildings is feasible for 3D modeling of the data acquired by different data acquisition techniques such as 3D laser scanners, photogrammetry and thermal sensing. Automated 3D geometric modeling of buildings using a laser scanner to create as-built BIM has been investigated in previous research [4]. The process is generally divided into three stages; in the first, the data is collected through a laser scanner placed in different locations around or throughout the building. In the second stage, data is processed by removing noise and combining the point clouds in one model. In the final stage, which is the most time consuming, the BIM is created for the building/facility. The process of creating the BIM itself is further divided into three stages; geometric modeling, assigning object material and category, and creation of objects relationships. Geometric modeling is the process of constructing simplified representations of the 3D shape of building components, such as walls, windows, and doors, from point cloud data.

One of the techniques used to speed up the modeling process is using a template of repeated objects and model additional repeated instances. However, this could be risky as the instances might contain slightly different geometry, which will cause errors. Knowledge about features such as sizes, positions, orientations, topology, and point density can speed up the modeling [33]. This was illustrated in a research to automate the reconstruction of a highly detailed polyhedron building façade model using data acquired from terrestrial laser scanner. The main challenge in the recognition of structural components was distinguishing relevant objects from occlusions and clutters. Planar features were first extracted as segments from raw laser point cloud. Generic knowledge of building façades, planar feature was later classified into various semantic features such as walls, doors, roof etc. Then, polygons of each semantic feature were generated and used to assume geometry in occluded area. Finally, a geometric and semantic rich polyhedron model was generated. Models of six semantic features were used including wall, door, roof, protrusion, intrusion and window, which are considered the most important elements on building façades [33].

Moreover, Xiong et al. [34] used a different and relatively faster approach where they applied an algorithm that can identify and automatically model the visible structural components for the indoor objects such as walls, floors, roofs, windows and doors of a building. The study was done on a "highly cluttered" building with forty different rooms, and the semantic BIM model was developed in three stages; data acquisition, data processing, and geometric modeling. This method classifies and models planar walls, floors, windows, and doors from the point cloud. This research also addressed occlusions and clutters. For occlusions, a ray-tracing algorithm was used to distinguish them from registered viewpoints and openings in the surfaces. Then, an in-painting algorithm was used to fill in the occluded regions with a realistic surface for visualization purposes. For clutter identification, the model learned to distinguish between surfaces that were clutter look-like and walls, roofs, and floors. The modeled objects were tagged with identity labels (e.g., wall) and metadata, surface material (e.g., concrete), and spatial and functional relationships between surrounding structures and spaces were established.

2.3 Material and texture extraction

Away from data collection and generation of the 3D geometric information, and in order to ensure a semantic rich as-built BIM model that is valuable, extraction of properties additional to the 3D geometric information, such as material and spatial relationship, are also beneficial for construction activities, such as progress tracking and facility management [6]. Surfaces made of different materials can share the same texture patterns [35], and similar shapes can be made up of different construction materials. For example, a rectangular box can represent a pad footing as well as formwork section. On the other hand, objects of a same material can have high shape variability; for instance, columns, beams, and slabs can be all made of concrete. The visual appearance of a surface depends on several factors: the illumination conditions, the geometric structure of the surface sample at several spatial scales, and the surface reflectance properties, often characterized by the bidirectional reflectance distribution function (BRDF) [36]. As mentioned before, laser scanning point clouds do not provide information that is helpful to understand textural and material properties of the objects. Materials such as glass, plastic, machined metals, and marbles can be problematic in the laser scanning processes due to insufficient reflected laser beams [33], [37]. Dimitrov et al. [6] proposed a method for distinguishing objects materials for use in construction control and monitoring. They created a new large building materials library which allows the recognition of different material types recorded in a variety of as-built contexts. The dataset of the created Construction Material Library (CML) was organized in three classes; material categories, which accounts for 20 major construction materials, and sub-categories, where the categories were further broken down into sub-types. This method can support the production of surface and solid geometric materials (SGM) by assembling adjacent 3D elements of the same material into full objects.

Nevertheless, due to the wide ranges of patterns a material can display, it is a challenging task to find good features to distinguish material categories [35]. The problem of recognizing or distinguishing materials from photographs has been addressed earlier in the 1960s where it was referred to the context of reflectance estimation [36]. Knowing only the reflectance properties of a surface may not be sufficient for determining the type of material of a building element. For instance, the fact that the surface of a material is smooth and shiny, doesn't necessarily tell us that it is made of metal. Moreover, material identification is related to texture recognition; however, surfaces made of different materials can share the same texture patterns.

Generally, the texture interpretation of images is not easy to describe or classify, which makes it more challenging task to train a machine to do it. Nevertheless, over the past decade, multiple striving efforts have been made to make computers acquire, understand, index, and interpret images expressing a wide variety of concepts, with much progress [19]. Main bases of difficulties include variable and sometimes uncontrolled imaging situations, complex and hard-to-describe objects in an image, objects occluding other objects, and the gap between arrays of numbers representing physical images and conceptual information perceived by humans. Creating automatic image classification algorithms has been an important research topic for decades in fields such as, space sciences, web searching, geographic information systems (GIS), biomedicine, surveillance and sensor systems, commerce, and education [19], [20], [21].

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 multiscale image representations are discrete wavelets, Gabor wavelets, dual-tree complex, Grey Level Concurrence Matrix (GLCM), and contourlets [22]. All of these approaches fall under the spatial-frequency image transform, where the image is decomposed into sub-images displaying multiple scales, frequencies and orientations of image details and structures using linear filter banks and down or up sampling operators [39].

2.4 Heat and water leaks detection

Building deterioration prompted by material degradations, moisture invasions, or water leakages are the main causes of energy inefficiency in many existing buildings [40]. In order to select suitable retrofits, it is essential to cautiously diagnose and investigate building zones in necessity of improvements. Furthermore, to reliably record and explore as-is energy performance in buildings, an effective documenting and visualization framework is needed to provide diagnostic results that can show the as-is building conditions to owners through retrofit management processes.

Over the past decades, and until now, many studies have been conducted in order to find efficient techniques that can help to detect and gather information about faults and leakages in buildings. A traditional method for leak detection is the acoustic pulse reflectometry, in which transducers detect the soundwaves, transform them from mechanical to electrical, forming resultant Root-Mean-Square voltages, which can be tracked. The expansion and growth of a leak is determined by the increase of these RMS voltages [41]. However, there are many limitations of this method such as the experience of the technician to differentiate leak noise from other noises, attenuation of acoustic pulses by sound waves, and difficulty of using the method in inaccessible areas.

The tracer gas technique is another technique that works by injecting a helium or nitrogen-hydrogen mix gas into the water network by supplying pressure. Using a spectrometer, the water that escapes the water pipes is detected. The drawback of this method is that the gas must be injected in the water pipe network and then track the pipes from the as built drawing to the target, which requires time and labor and correct and up-to-date data [42].

Other popular leak detection techniques include leak noise correlators [43], and use of a Ground Penetrating Radar (GPR) [44]. However, another important issue – which is often not considered–is that the deterioration rate of building assemblies typically varies even over small surface areas. For instance, when it comes to building envelopes, various regions across the surface may suffer from different levels of degradation. As such, their conditions would change differently over time. Therefore, a method for building diagnostics should assess and visualize the as-is building conditions at point-level across geometrical forms of the building elements so that defects can be precisely detected and localized.

2.4.1 Thermal Infrared sensing and spectrometry

Thermal inspection is a tremendous method for examination of unusually hot or cold zones of an object, maintenance of electrical and mechanical systems, areas of corrosion weakening on plant carrying hot gas or liquid, inspection for fouling or internal plugging of piping systems, checking the quality of refractory coatings, leak detection, composition changes and condition monitoring of laminates and many others [45]. The nondestructive testing nature of this method allows large areas to be surveyed rapidly in real time. This method can also be used as an anticipatory monitoring tool to determine the fresh possible failure. It can measure and detect regions that are sometimes uneasy to survey by other methods [45], [46].

Balaras et al. [40] took advantage of thermal IR and illustrated a methodology to utilize IR in building diagnostics with an emphasis on how it was implemented to support office building audits following the European TOBUS building audit methodology [47]. To demonstrate common problems, the paper presented examples of IR procedure for building envelope, mechanical and electrical inspections in the audited office buildings.

Grinzato et al. [48] presented a methodology of quantitative infrared thermography for building diagnosis based on the solution of the inverse heat transfer problem, for the detection and evaluation of flaws in buildings. Time and change in temperature were recorded by a thermographic equipment and each pixel that belongs to the examined area was processed quantitatively. Data were mapped too, in order to detect defects in walls, based on the most suitable local thermal parameter. Simplified models were described to interpret surface temperature data in order to study physical defects. The building envelope was examined mainly in transient thermal regime. Periodic or pulse heating of the surface tests were carried out. Temperature evolution was predicted using theoretical analysis. Experimental results were reported for insulation deficiencies and thermal bridges evaluation, air leakage detection and moisture content mapping.

Calculation of the heat transfer for an existing building is another complex task, due to the inaccessibility or lack of information available about the materials and their thickness [49]. In another study, Lagüela et al. [50] used a GbXML schema along with the use of visual recognition process as a standard output for the as built BIM model, created from geometric and thermographic data. Prior to creating the as built BIM model, the information went through two processes, which were data acquisition and data processing. For the geometric modeling, the data was acquired through laser scanning, and then was filtered, registered, and processed as boundary points. For the thermal characterization, infrared thermography was applied as a quantitative approach using a thermograghic camera for the walls and roofs and then processed as U-values. The U-values are coefficients of transmission of heat through the materials, which have become standard for energy analysis. Finally, a thermally-characterized as-built BIM model was formed, where the U-values provided a descriptive data associated with the elements type.

Chapter 3: Materials and Methodologies

3.1 Materials

3.1.1 BIM model description

Data collected in this project include thermal images of the interior walls of the fourth floor in Tower C of the test facility, Mafraq Hospital. Description of the test facility is provided in the following section. The BIM of the test facility was created with Autodesk Revit software. Autodesk Revit is a Building Information Modeling (BIM) software that allows the users to design a building structure and its components in 3D environment, provides 2D annotations, and extracts building information and quantities from the model's integrated database. The level of development (LOD) of the BIM model is 400 which includes the accurate quantities, shapes, sizes, locations and orientations of the structural elements. The full integrated model consists of architectural model, structural model, interior model, Mechanical, Electrical, Plumbing (MEP) model, and Façade model. However, the only models used in this project were the architectural, the structural, and the façade models. This was due to the fact that the other models have not yet been implemented in the test facility. Figure 5 shows a snapshot of the BIM model of the test facility.

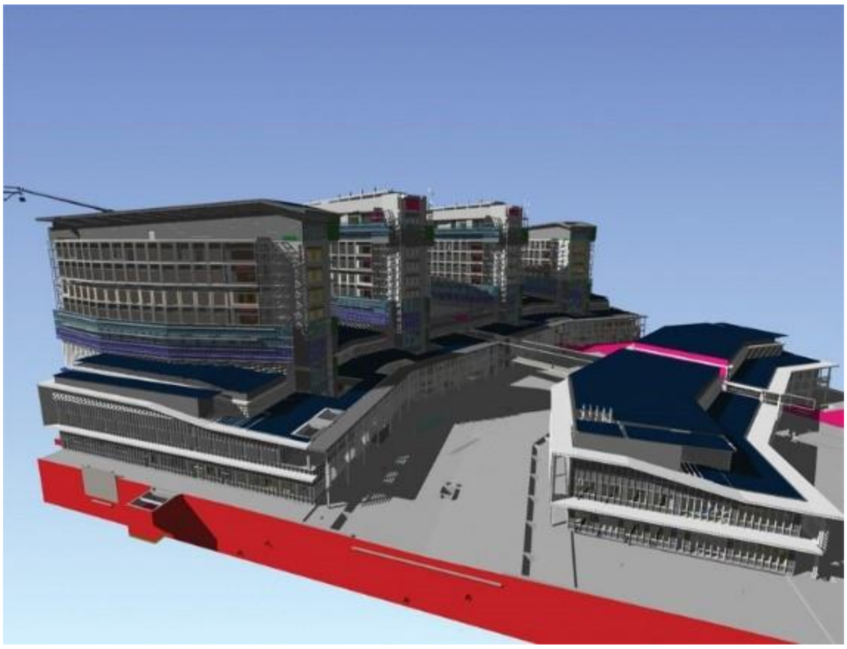


Figure 5: Snapshot of the 3D model of the BIM of the test facility

3.1.2 Description of the test facility

The test facility is the Mafraq Hospital; a 739 bed general hospital in the Mafraq area of Abu Dhabi, United Arab Emirates (UAE), which has an estimated construction cost of a 600 US million dollars. The building is under construction in its latest stages. The hospital consists of a two-storey basement including service accommodation, laboratories, central sterile services department (CSSD), dining and parking, and a three-storey outpatient building. This building includes clinics, a link bridge, a three-storey podium building that includes diagnostics units, operating theatres, ER unit, rehab unit, ICU and maternity units. It also includes two nine-storey and two eleven-storey inpatient towers, peripheral buildings including substations, cooling plant, workshop, mortuary, underground tanks and service tunnels. Figure 6 shows snapshot of the completed building of the Mafraq Hospital and the construction status as of January 2015.

Figure 6: Mafraq Hospital as of January 2015

The thermal images acquired in this project were for part of the fourth floor in Tower C of the hospital. Figure 7 shows the layout and a three-dimensional (3D) view of the section of the fourth floor in which the experiment of the project was carried out.

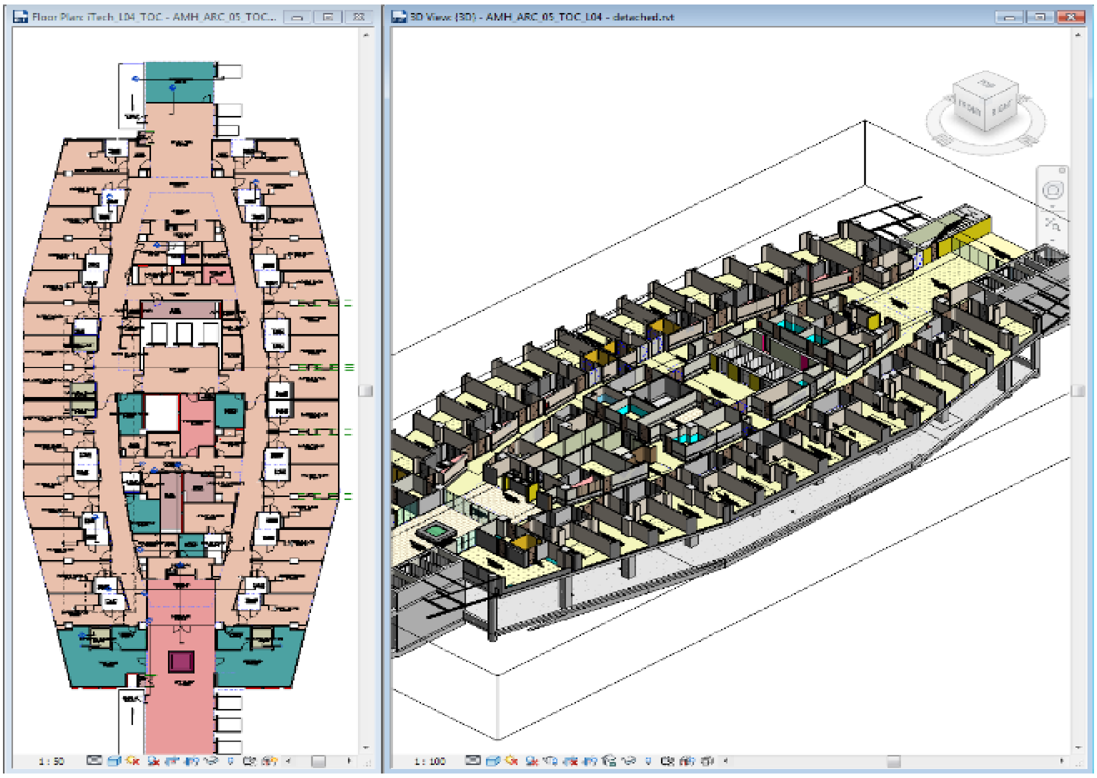


Figure 7: Layout and 3D view of section of fourth floor of Tower C

3.1.3 Data acquisition

There are many advantages of using thermal infrared remote sensing techniques. For example, unlike visible and near infrared (NIR), images can be acquired at any time of the day or night independent of the sun as an illumination source. In building construction, thermal infrared imaging has been playing an essential role in detecting heat leaks of thermal insulations as well as water and waste water leaks. In this project, A FLIR T640 Infrared camera (Figure 8) was used to collect thermal imagery of the internal walls of part of fourth floor of tower C in Mafraq Hospital. Detailed technical specifications of the FLIR T640 Infrared camera are listed in Table 1.

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 [46]. Data acquisition was performed in the afternoon at a temperature of 25°C and relative humidity of 58%. Images were acquired for all of the internal walls in the rooms of the fourth floor in tower C, and some of the basement (parking) area walls. 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.

Figure 8: The FLIR T640 camera

3.2 Methodologies

In this study, infrared thermal images were collected for the interior walls of the test facility; Mafraq Hospital. The images were then processed using the techniques described in the following sections in order to extract material and texture information of the walls and further integrate that into the BIM model of the hospital.

Table 1: FLIR T640 IR camera technical specifications [51]

Feature	**Description**
Measurement presets	6 presets: center spot; hot spot (box max); cold spot (box min): no measurements; user preset 1; user preset 2
Frame rate	30Hz
Field of view/minimum focus distance/FOV Match	25° x 19° / 0.25m / Field of View Match where Digital Image FOV adapts to the IR lens
Detector type - focal plane array (FPA) uncooled microbolometer	640 x 480 pixels
Spectral range	7.5 to 14µm
Lens	25° or 45° models (optional 7°, 15°, 25°, 45°, 80°, Close up 100µm, 50µm lenses available)
Display	Built-in touch-screen 4.3" color LCD (800 × 480 pixels)
Manual image adjustment	Level/span/max/min
Measurement modes	10 Spotmeters, 5 Box areas, Isotherm, Auto hot/cold spot, Delta T
Measurement correction	Reflected ambient temperature & emissivity correction
GPS	Location data automatically added to every image from built-in GPS
Dimensions/weight	143x196x94mm/1.3kg, including battery
Resolution	Crisp thermal images with 307,200 pixels (640 x 480}
Accuracy	Calibrated within +/– 2°C or +/– 2% of reading
Temperature range	-40°C to 2000°C (-40°F to 3632°F)

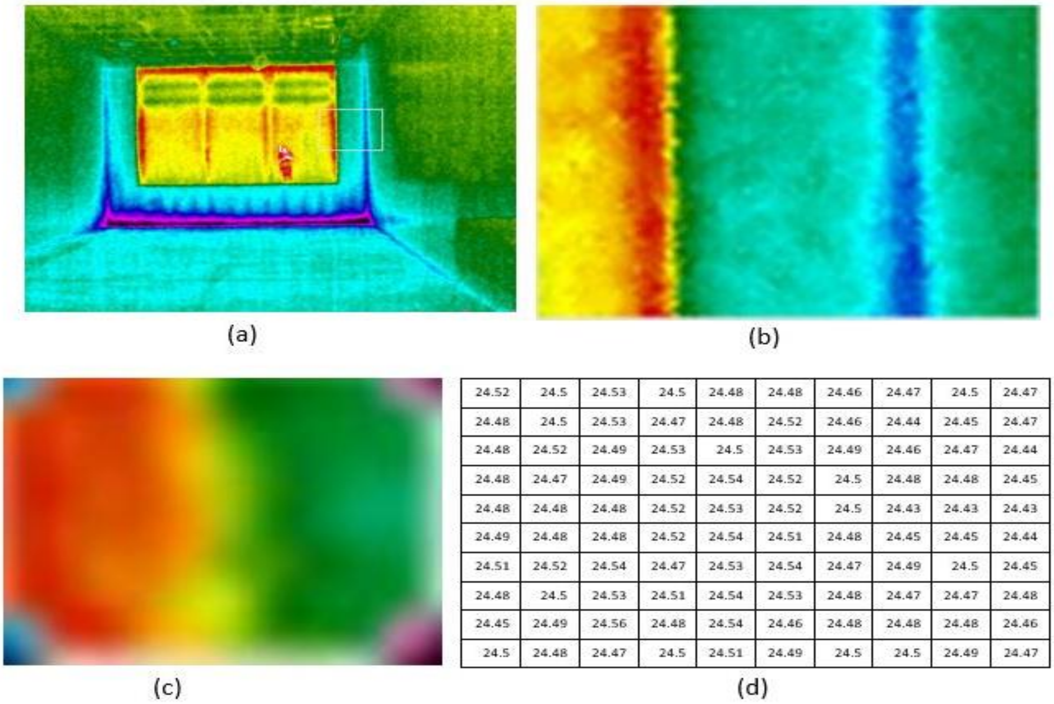
3.2.1 Data processing

Once all of the thermal infrared images were acquired, thermal and material information was extracted by texture referencing of thermal information at each pixel in the images. Feature extraction means simplification of the volume of resources essential to define a large set of data, correctly. 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 of the test facility. Data processing was divided into three stages, which were: (1) exploration, (2) model building and validation, and (3) texture and material information extraction. The exploration stage involved feature extraction and basic image processing using the FLIR Quick Report v1.2 software. In the model building stage, the outcome of the previous stage was analyzed in order to identify the materials of the imaged walls. In the final stage, texture and material information of the interior walls was extracted. The details of the different stages of data processing phase of this study are presented in the following sections.

3.2.1.1 Exploration

After acquiring the images, an image 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. The outcome of this process was raster models that of the radiance values that represent the emitted thermal infrared radiation, which can be converted into temperature at each pixel reflected ambient temperature, atmospheric temperature, humidity, and the length of the line of sight for each image. Figure 9 shows a sample thermal image (also known as thermographic image) and the basic information, which it contains.

Then, an algorithm for texture segmentation process was developed in this study and applied, which automatically extracts textural information needed for identification of the materials of the walls. This texture segmentation algorithm splits the image into different homogeneous texture regions (see Figure 10). The Python code of the texture segmentation algorithm is shown in Appendix I. The outcome of this process was raster models that represent the emitted thermal infrared radiation at each pixel of the targeted material (interior gypsum board, in this case, as shown in Figure 10) in the thermal image.



24.52	24.5	24.53	24.5	24.48	24.48	24.46	24.47	24.5	24.47
24.48	24.5	24.53	24.47	24.48	24.52	24.46	24.44	24.45	24.47
24.48	24.52	24.49	24.53	24.5	24.53	24.49	24.46	24.47	24.44
24.48	24.47	24.49	24.52	24.54	24.52	24.5	24.48	24.48	24.45
24.48	24.48	24.48	24.52	24.53	24.52	24.5	24.43	24.43	24.43
24.49	24.48	24.48	24.52	24.54	24.51	24.48	24.45	24.45	24.44
24.51	24.52	24.54	24.47	24.53	24.54	24.47	24.49	24.5	24.45
24.48	24.5	24.53	24.51	24.54	24.53	24.48	24.47	24.47	24.48
24.45	24.49	24.56	24.48	24.54	24.46	24.48	24.48	24.48	24.46
24.5	24.48	24.47	24.5	24.51	24.49	24.5	24.5	24.49	24.47

Figure 9: Basic information of thermographic image: (a) Original 640 x 480 pixel image. (b) Enlargement showing 100 x 100 pixel image (c) Enlargement 10 x 10 pixels image (d) Part of the image attribute table showing temperature values at each pixel

3.2.1.2 Model building and validation

The objective of this part of the methodology was 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 [45]. A common approach for estimating the statistical characteristics of such a variable is the Monte Carlo Simulation method [44]. 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 makes Monte Carlo Simulation a suitable approach that can help in segmenting each image and further identifying the materials of the interior walls.

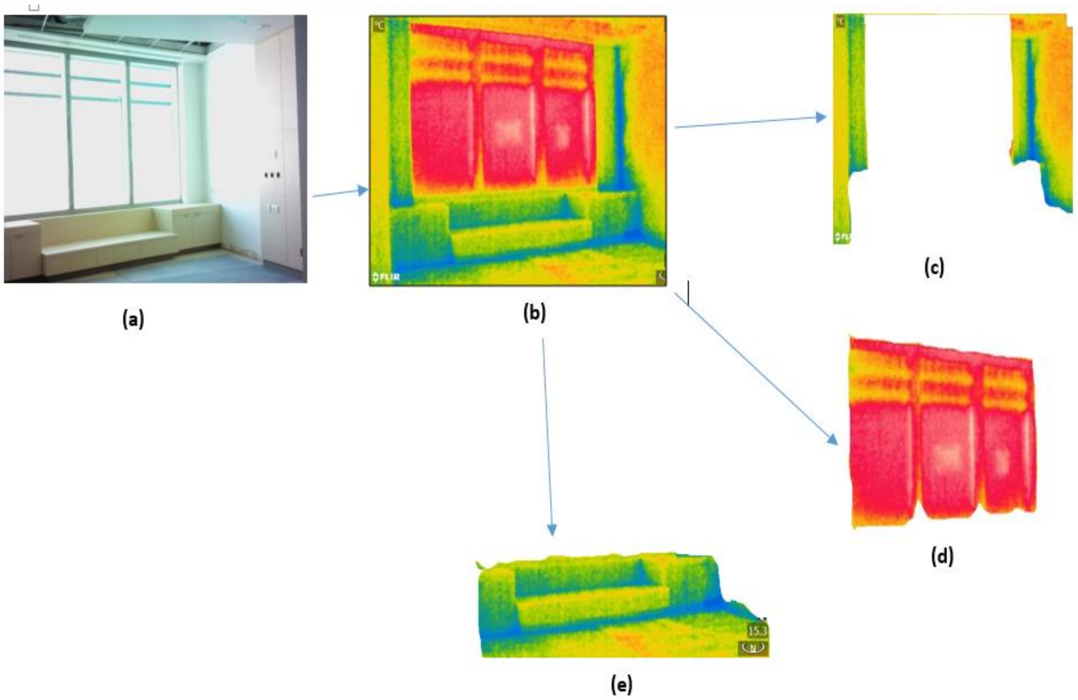


Figure 10: Texture extraction and feature labeling of an interior gypsum board wall and window in a thermal image: (a) Original digital image; (b) Corresponding thermal image; (c), (d), & (e) Wall features isolated from the rest.

In this study, 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 each material (interior gypsum board and concrete) in order to classify each radiance matrix accordingly (i.e. processed thermal images). This process later helped in identifying the materials of the imaged walls. Since only interior walls were used in this study, two common material types of interior walls were identified and used, which were interior gypsum board and concrete. The size of the window of the material models used to search these radiance matrices were 20 x 20 pixels, which was suitable size given that materials of interior walls normally don't vary within such a distance in normal circumstances. Figures 11, 12, and 13 show examples of digital images and the corresponding thermal image of gypsum board and concrete; the two main material types used in this study.

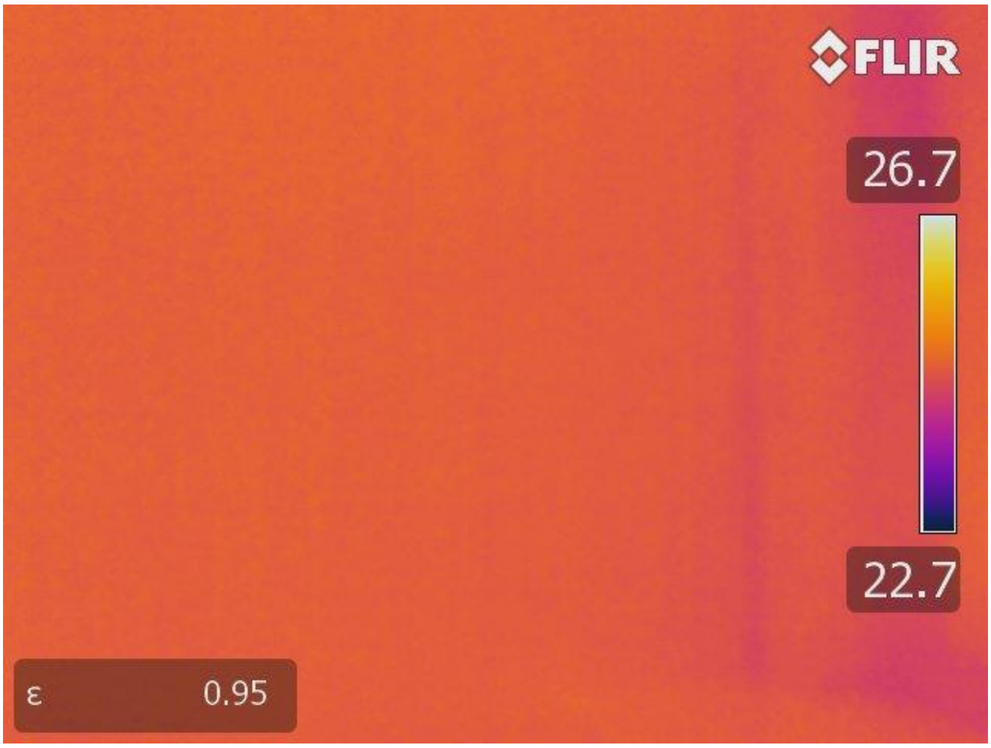
3.2.1.3 Texture and material information extraction

The final stage of data processing comprised of using the best models identified in the previous stage and applying them to the rest of the processed images of the interior walls. The outcome of this process was the prediction of the materials of the interior walls identified based on the statistical characteristics and the models of gypsum board and concrete. Once all the processed images have been transformed into data that represent the texture and the material of the imaged walls, this information was exported into MS Excel and sorted according to each walls unique identifier in preparation for texture and material integration into the Revit-based BIM model of the test facility. The following section describes the way in which texture and material information were integrated into the BIM model of the test facility.

3.2.2 Integration of the extracted information into the BIM model

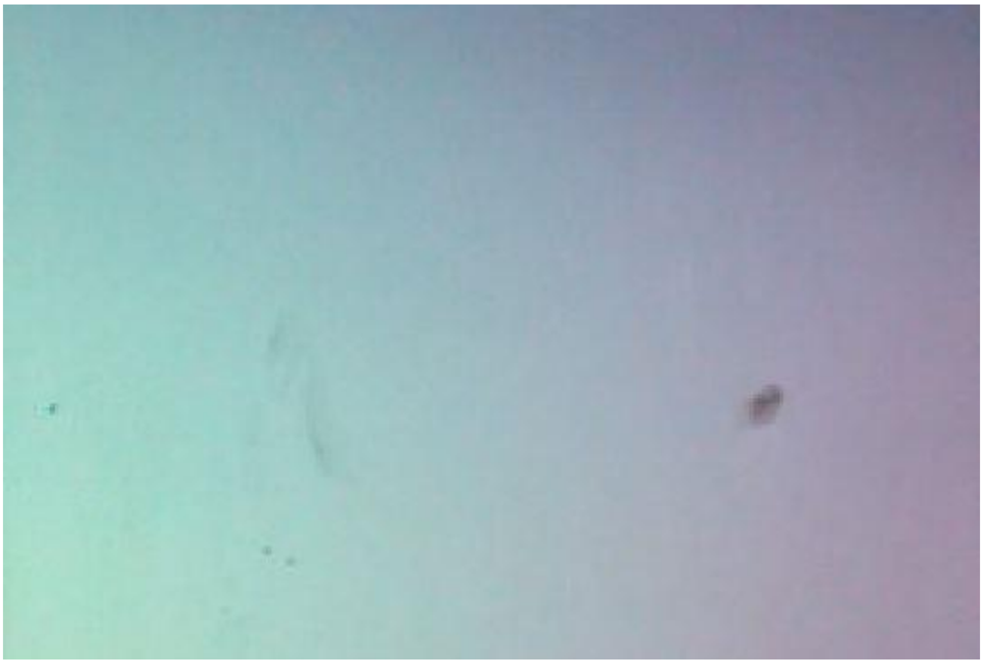
In the relational database of the Revit-based BIM model of the test facility, two new project parameters were created for the interior walls, which were “Surface Texture” and “Surface Material.” Since Revit software doesn’t define the texture of the modeled elements in the BIM model, the type of new parameter defined in this case was “Text,” which was grouped under “Energy Analysis.” This means that the texture of the interior walls was described in “text” format in the Revit-based BIM database of the hospital. On the other hand, and since Revit has a built-in material library, the new parameter for material was defined as “Material,” was grouped under “Materials and Finishes,” and was mapped to the existing material library in the Revit-based BIM database (refer to Figure 14).

(a)



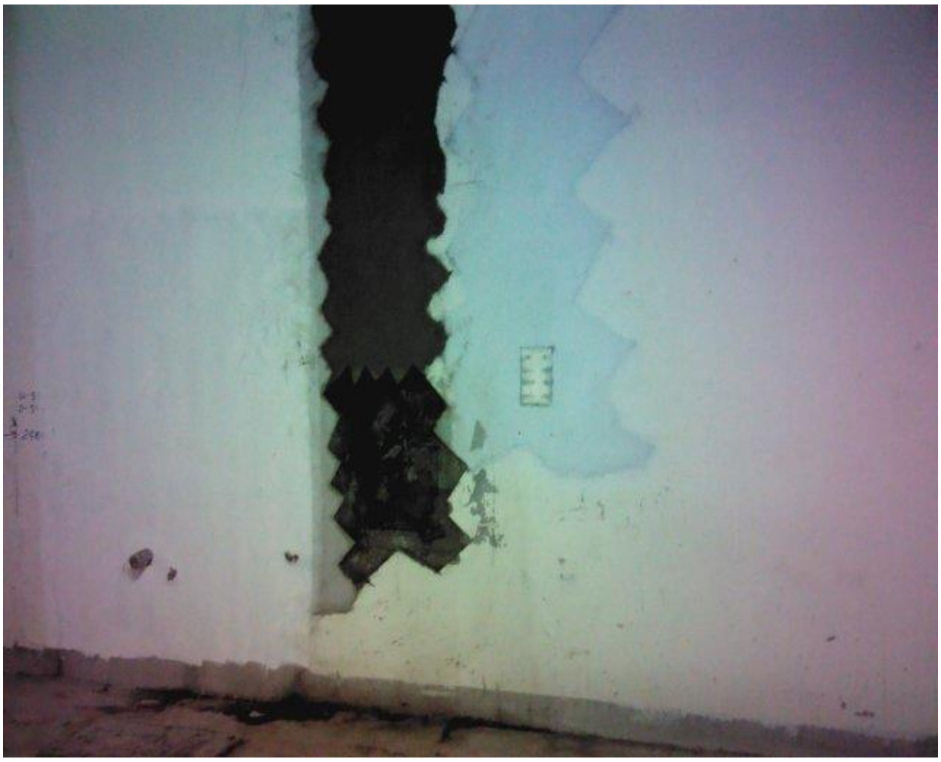
(b)

Figure 11: (a) Digital RGB image of gypsum board, and (b) the corresponding thermal image.

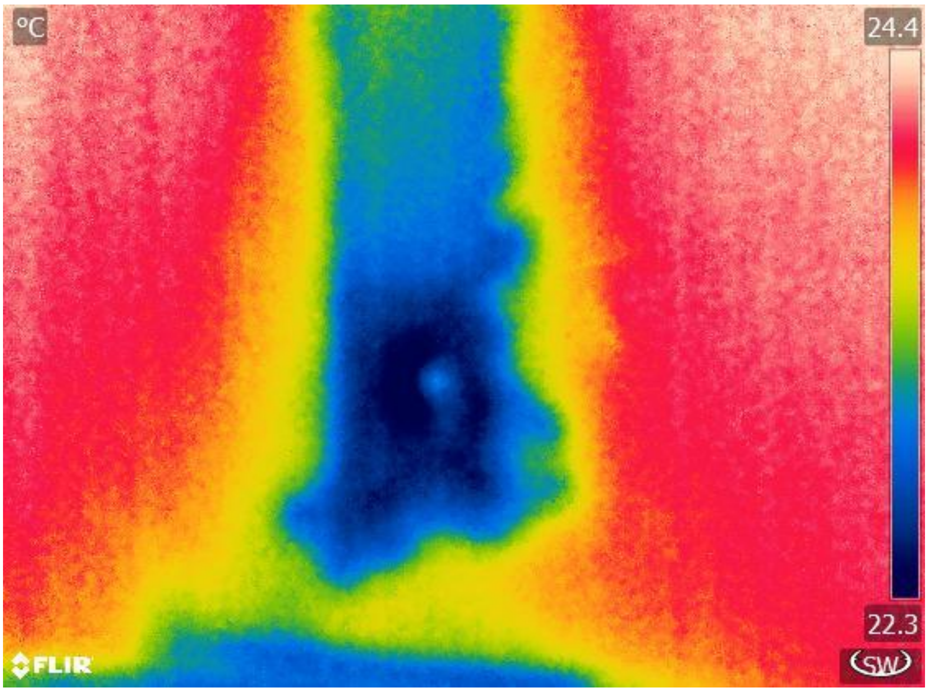


(a)

Figure 12: (a) Digital RGB image of concrete wall, and (b) and the corresponding Thermal image

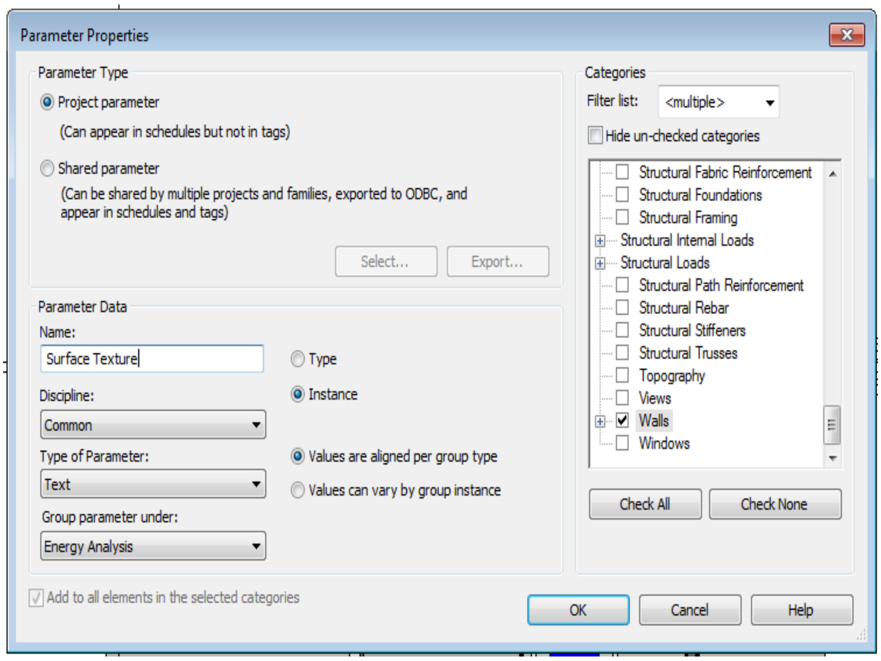


(a)

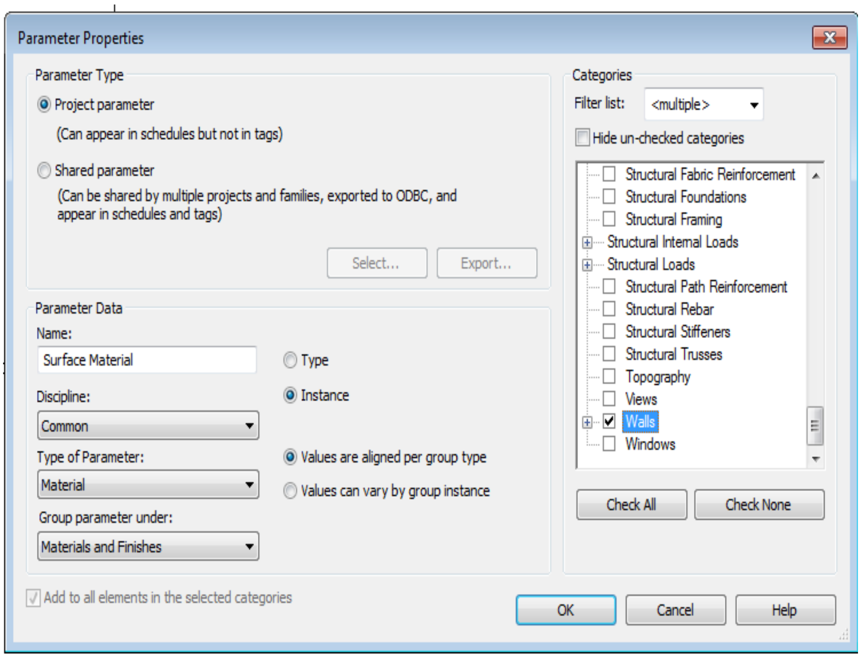


(b)

Figure 13: Digital image of a nonhomogeneous concrete wall and the (b) corresponding thermal image.



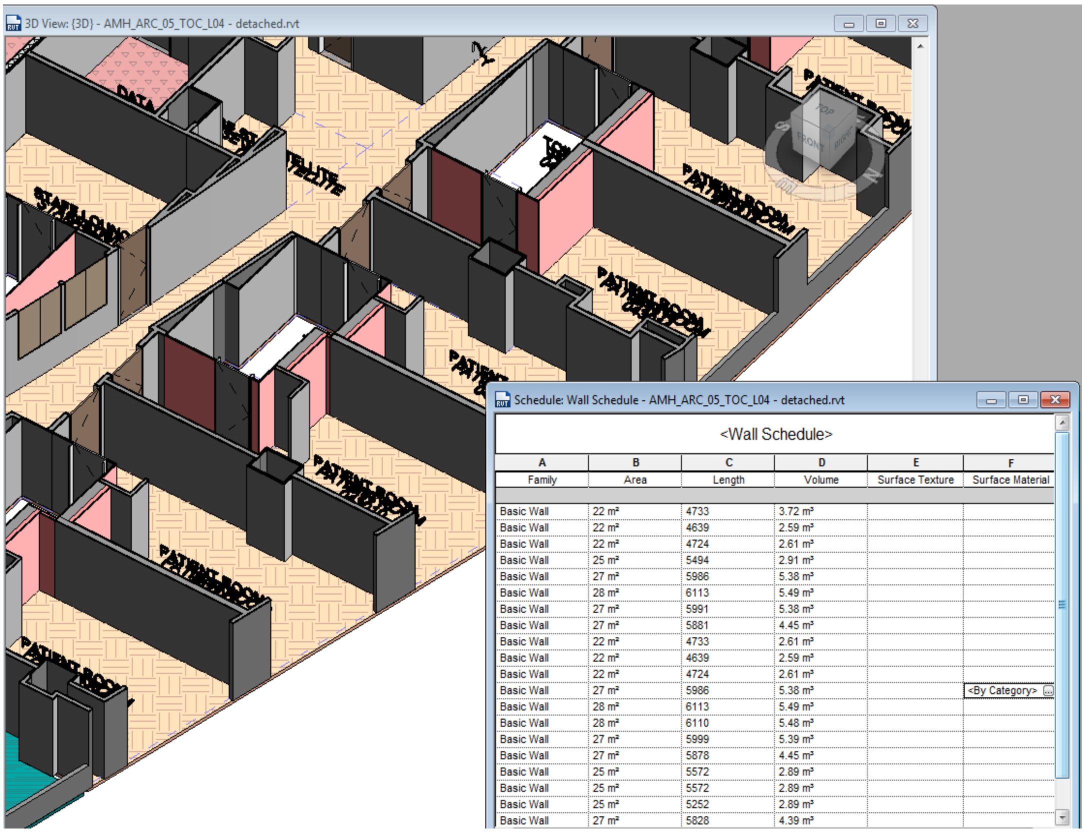
(a)



(b)

Figure 14: Parameter properties box showing the new parameters; (a) Surface texture, (b) Surface material

A schedule of the interior walls was then created in the Revit database of the BIM model of the hospital, which included the following parameters: Elements ID, Family Name, Area, Length, Volume, Surface Text, and Surface Material in Revit. Figure 15 shows a sample of the schedule created in Revit for the interior walls.



A	B	C	D	E	F
Family	Area	Length	Volume	Surface Texture	Surface Material
Basic Wall	22 m²	4733	3.72 m³		
Basic Wall	22 m²	4639	2.59 m³		
Basic Wall	22 m²	4724	2.61 m³		
Basic Wall	25 m²	5494	2.91 m³		
Basic Wall	27 m²	5986	5.38 m³		
Basic Wall	28 m²	6113	5.49 m³		
Basic Wall	27 m²	5991	5.38 m³		
Basic Wall	27 m²	5881	4.45 m³		
Basic Wall	22 m²	4733	2.61 m³		
Basic Wall	22 m²	4639	2.59 m³		
Basic Wall	22 m²	4724	2.61 m³		
Basic Wall	27 m²	5986	5.38 m³		<By Category>
Basic Wall	28 m²	6113	5.49 m³		
Basic Wall	28 m²	6110	5.48 m³		
Basic Wall	27 m²	5999	5.39 m³		
Basic Wall	27 m²	5878	4.45 m³		
Basic Wall	25 m²	5572	2.89 m³		
Basic Wall	25 m²	5572	2.89 m³		
Basic Wall	25 m²	5252	2.89 m³		
Basic Wall	27 m²	5828	4.39 m³		

Figure 15: Example of a schedule created in Revit for the interior walls

Then, the wall schedule was exported into MS Excel using a tool called Ideate BIMLink. The Ideate BIMLink is a third party tool that can be installed and integrated in Autodesk Revit. It allows users to extract data from a Revit file into Microsoft Excel and to export the updated 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 created parameters in the Revit database file of the interior walls in the BIM model of hospital.

Chapter 4: Results and Discussion

4.1 Exploration Results

After acquiring the images, the first step was to enter all the images into the FLIR QuickReport for pre-processing, which included geometric corrections of images taken with slightly different orientation with the line of sight slightly off the horizontal. Using FLIR QuickReport software tools, emitted thermal infrared radiation can be recorded at different areas of the walls and then converted into temperature values, and therefore exported to MS Excel as full matrix (full image), partial matrix (an area), or row or column (a line), depending on the user interest. The emitted thermal infrared radiance, emissivity, ambient temperature, atmospheric temperature, relative humidity, and line of sight distance are also provided as outcomes of the process. Figure 16 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. FLIR QuickReport provides ten different palettes that are shown in Figure 17.

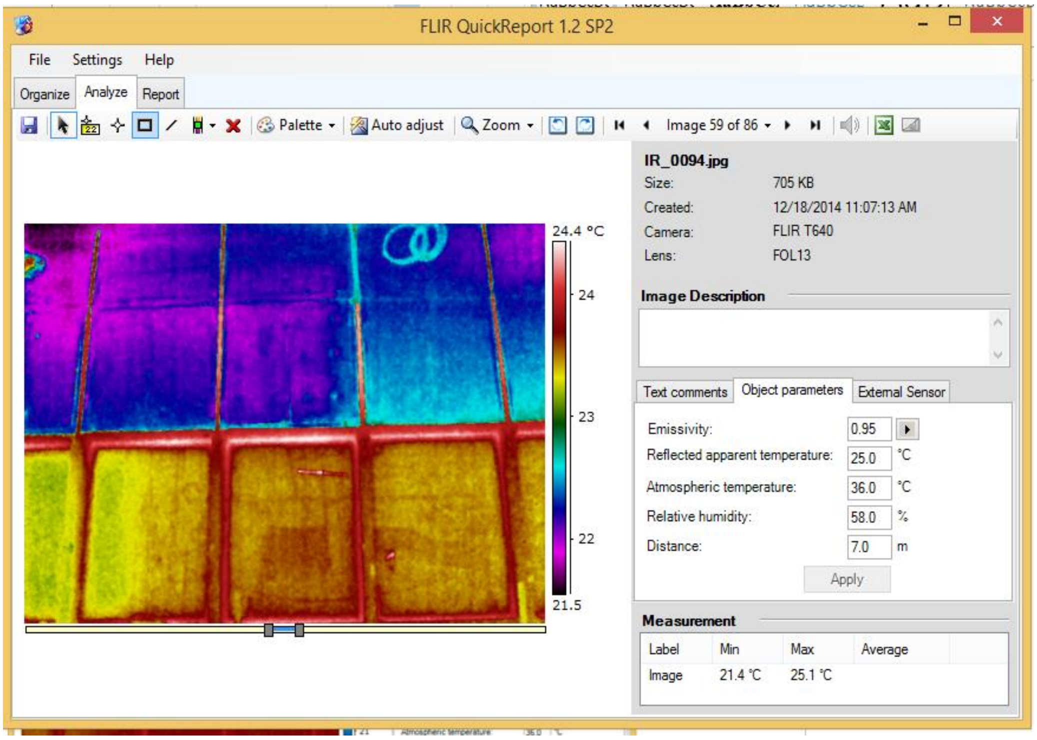


Figure 16: FLIR QuickReport window.

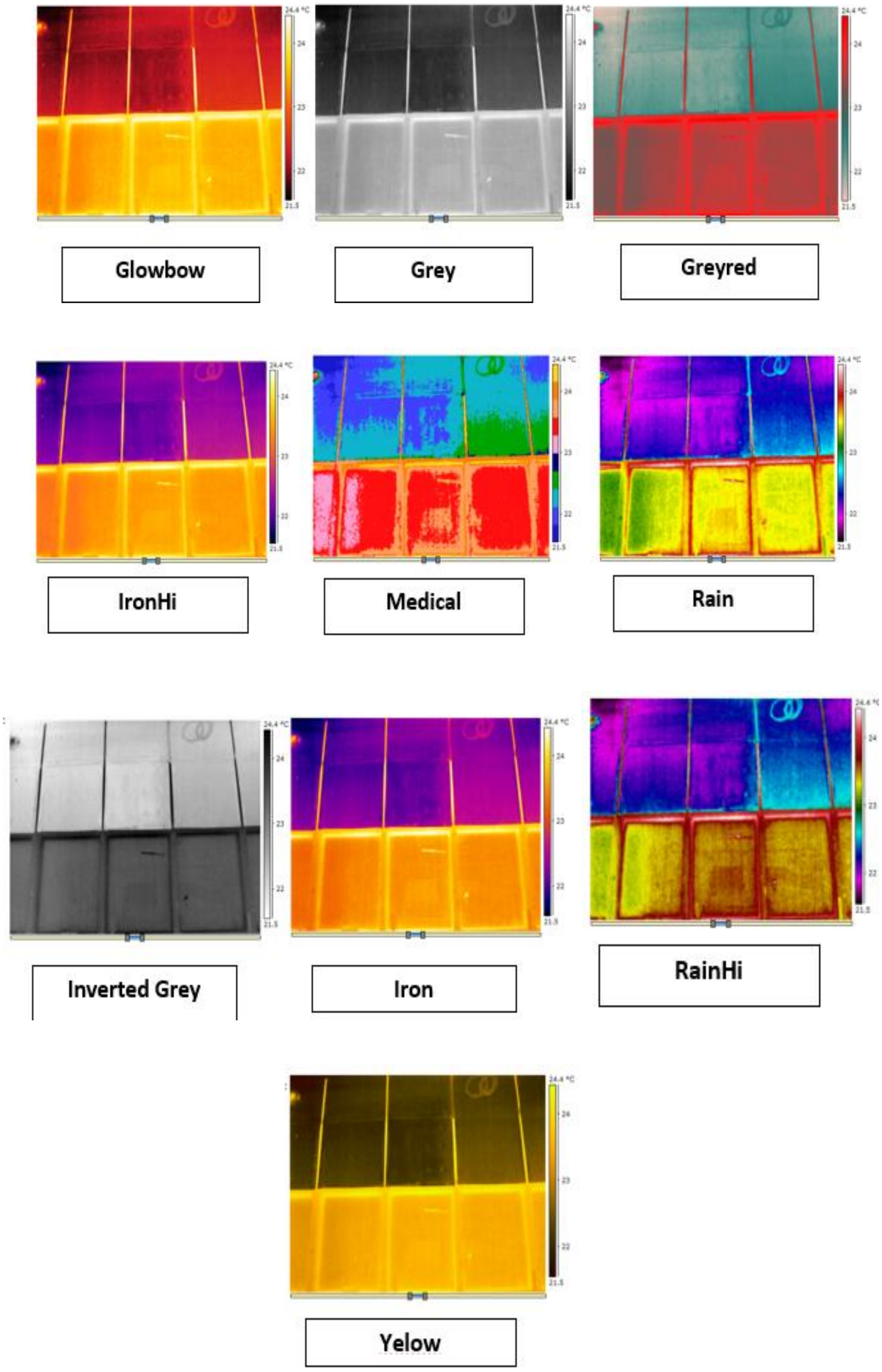
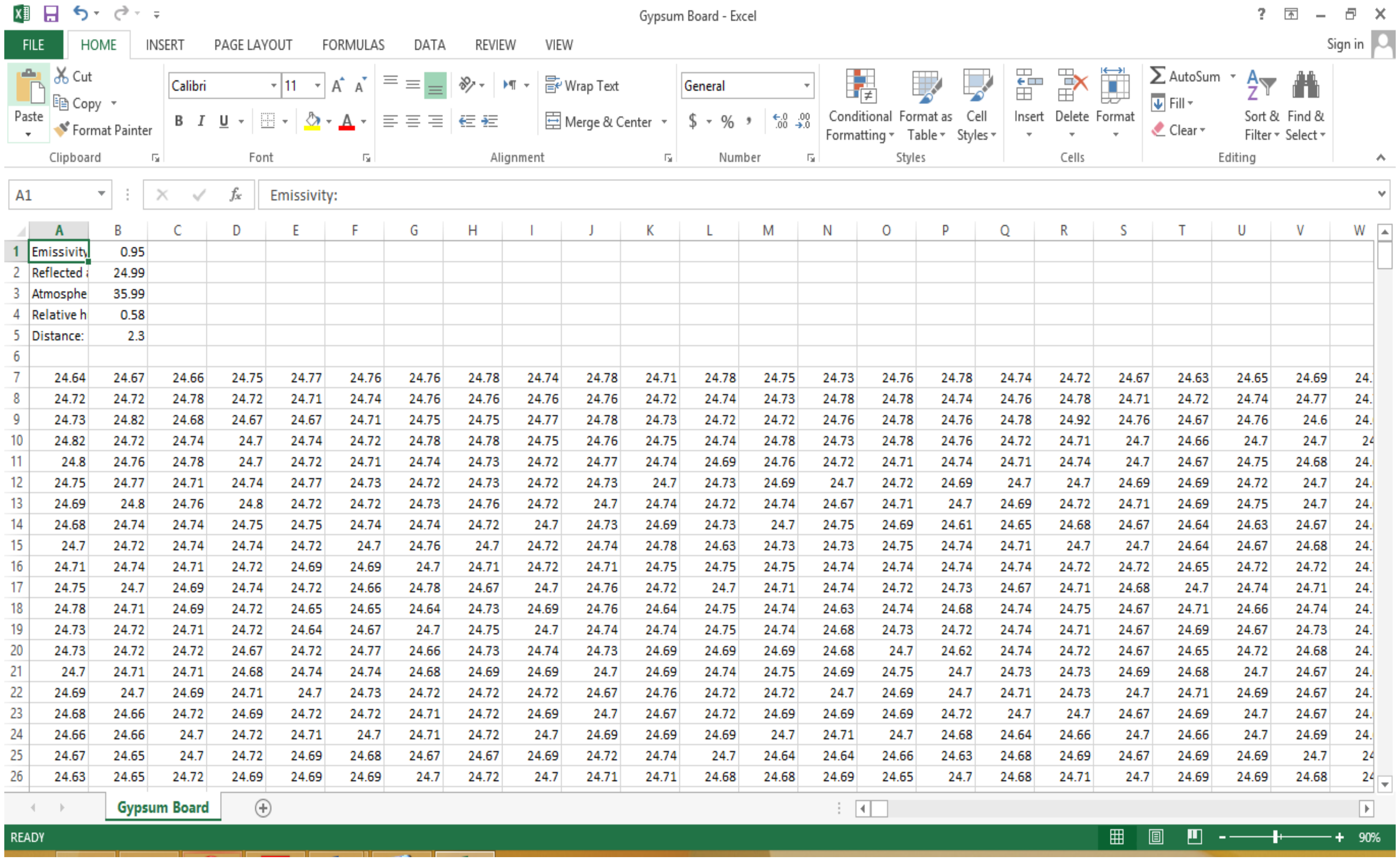


Figure 17: Different palette applied to the image in figure 16 produced by FLIR QuickReport software

Also, FLIR QuickReport software provides an Excel sheet for every image processed with the Excel sheet cells that represent the pixels of the image such that each cell stores the emitted thermal infrared radiance values of the corresponding pixel, which are convertible to temperature values. In this project, this information was used to identify the material type of the interior walls. Figure 18 shows part of the Excel sheet produced for the image shown in Figure 16.

Since the focus of this study was the interior walls of the Mafraq Hospital, all non-walls data was not needed. An algorithm was created in Python and used to filter out all non-walls portions of the images (this Python is shown in Appendix 1). 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 the image is imported, the matrix is converted into an array where the image analysis takes place. Then, in the image analysis, the algorithm tries to find similar contours and common features, identifies it, and finally plots the results. Below is an example where the algorithm identified and further selected an interior wall from the rest of image components (Figures 19, 20, 21). Figure 19 shows a digital image of a concrete wall with a door opening and some steel scaffolding and an electric cable above the door. Figure 20 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 Python described in the previous section in order to extract only the wall as shown in Figure 21. Note that in the filtered image shown in Figure 22, the door opening, the steel scaffolding, and the electric cable were filtered out.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W
1	Emissivity	0.95																					
2	Reflected a	24.99																					
3	Atmosphe	35.99																					
4	Relative h	0.58																					
5	Distance:	2.3																					
6																							
7	24.64	24.67	24.66	24.75	24.77	24.76	24.76	24.78	24.74	24.78	24.71	24.78	24.75	24.73	24.76	24.78	24.74	24.72	24.67	24.63	24.65	24.69	24.
8	24.72	24.72	24.78	24.72	24.71	24.74	24.76	24.76	24.76	24.76	24.72	24.74	24.73	24.78	24.78	24.74	24.76	24.78	24.71	24.72	24.74	24.77	24.
9	24.73	24.82	24.68	24.67	24.67	24.71	24.75	24.75	24.77	24.78	24.73	24.72	24.72	24.76	24.78	24.76	24.78	24.92	24.76	24.67	24.76	24.6	24.
10	24.82	24.72	24.74	24.7	24.74	24.72	24.78	24.78	24.75	24.76	24.75	24.74	24.78	24.73	24.78	24.76	24.72	24.71	24.7	24.66	24.7	24.7	24
11	24.8	24.76	24.78	24.7	24.72	24.71	24.74	24.73	24.72	24.77	24.74	24.69	24.76	24.72	24.71	24.74	24.71	24.74	24.7	24.67	24.75	24.68	24.
12	24.75	24.77	24.71	24.74	24.77	24.73	24.72	24.73	24.72	24.73	24.7	24.73	24.69	24.7	24.72	24.69	24.7	24.7	24.69	24.69	24.72	24.7	24.
13	24.69	24.8	24.76	24.8	24.72	24.72	24.73	24.76	24.72	24.7	24.74	24.72	24.74	24.67	24.71	24.7	24.69	24.72	24.71	24.69	24.75	24.7	24.
14	24.68	24.74	24.74	24.75	24.75	24.74	24.74	24.72	24.7	24.73	24.69	24.73	24.7	24.75	24.69	24.61	24.65	24.68	24.67	24.64	24.63	24.67	24.
15	24.7	24.72	24.74	24.74	24.72	24.7	24.76	24.7	24.72	24.74	24.78	24.63	24.73	24.73	24.75	24.74	24.71	24.7	24.7	24.64	24.67	24.68	24.
16	24.71	24.74	24.71	24.72	24.69	24.69	24.7	24.71	24.72	24.71	24.75	24.75	24.75	24.74	24.74	24.74	24.74	24.72	24.72	24.65	24.72	24.72	24.
17	24.75	24.7	24.69	24.74	24.72	24.66	24.78	24.67	24.7	24.76	24.72	24.7	24.71	24.74	24.72	24.73	24.67	24.71	24.68	24.7	24.74	24.71	24.
18	24.78	24.71	24.69	24.72	24.65	24.65	24.64	24.73	24.69	24.76	24.64	24.75	24.74	24.63	24.74	24.68	24.74	24.75	24.67	24.71	24.66	24.74	24.
19	24.73	24.72	24.71	24.72	24.64	24.67	24.7	24.75	24.7	24.74	24.74	24.75	24.74	24.68	24.73	24.72	24.74	24.71	24.67	24.69	24.67	24.73	24.
20	24.73	24.72	24.72	24.67	24.72	24.77	24.66	24.73	24.74	24.73	24.69	24.69	24.69	24.68	24.7	24.62	24.74	24.72	24.67	24.65	24.72	24.68	24.
21	24.7	24.71	24.71	24.68	24.74	24.74	24.68	24.69	24.69	24.7	24.69	24.74	24.75	24.69	24.75	24.7	24.73	24.73	24.69	24.68	24.7	24.67	24.
22	24.69	24.7	24.69	24.71	24.7	24.73	24.72	24.72	24.72	24.67	24.76	24.72	24.72	24.7	24.69	24.7	24.71	24.73	24.7	24.71	24.69	24.67	24.
23	24.68	24.66	24.72	24.69	24.72	24.72	24.71	24.72	24.69	24.7	24.67	24.72	24.69	24.69	24.69	24.72	24.7	24.7	24.67	24.69	24.7	24.67	24.
24	24.66	24.66	24.7	24.72	24.71	24.7	24.71	24.72	24.7	24.69	24.69	24.69	24.7	24.71	24.7	24.68	24.64	24.66	24.7	24.66	24.7	24.69	24.
25	24.67	24.65	24.7	24.72	24.69	24.68	24.67	24.67	24.69	24.72	24.74	24.7	24.64	24.64	24.66	24.63	24.68	24.69	24.67	24.69	24.69	24.7	24
26	24.63	24.65	24.72	24.69	24.69	24.69	24.7	24.72	24.7	24.71	24.71	24.68	24.68	24.69	24.65	24.7	24.68	24.71	24.7	24.69	24.69	24.68	24

Figure 18: Part of the excel sheet produced by FLIR QuickReport of the image in Figure 16.

Figure 19: Digital image of concrete wall with door and some steel scaffolding

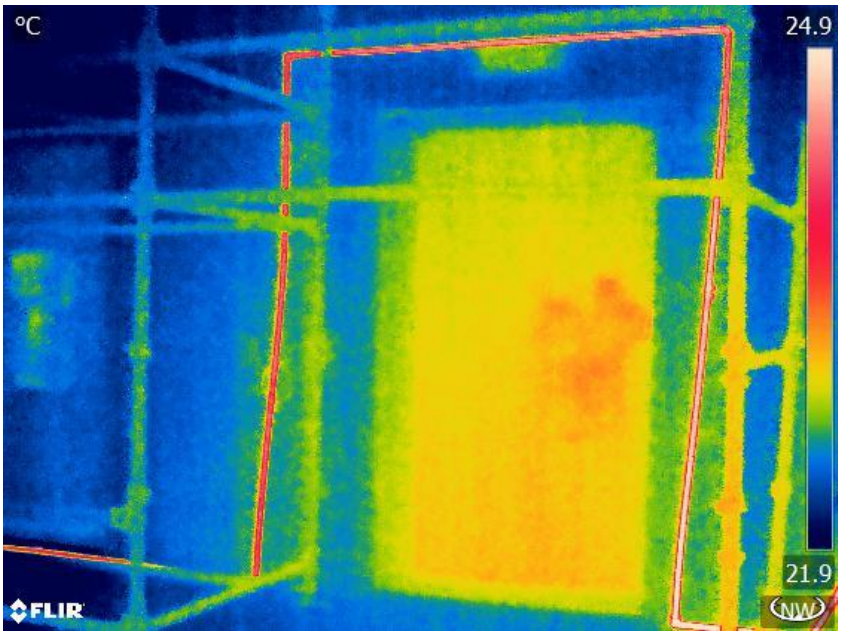


Figure 20: Thermal image of the thermal image of Figure 19.

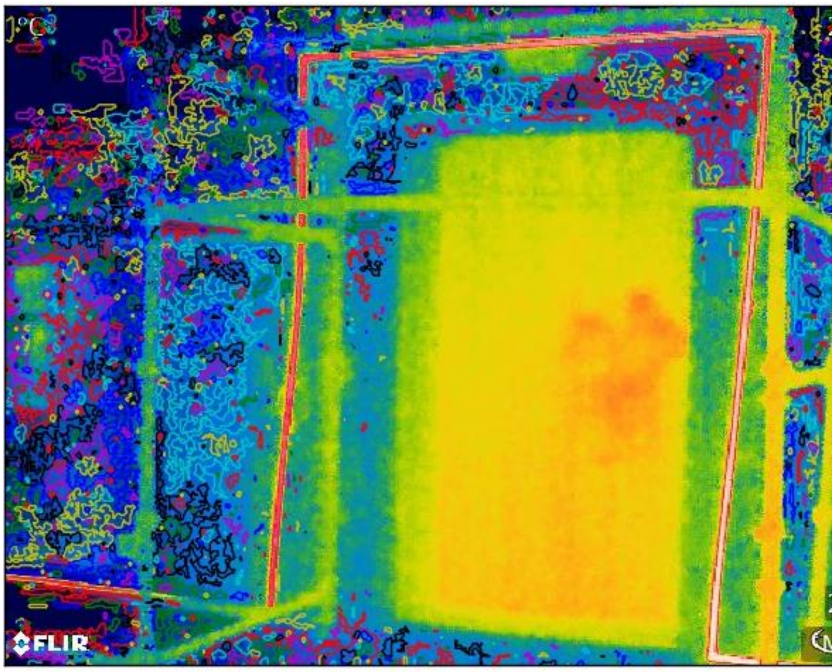
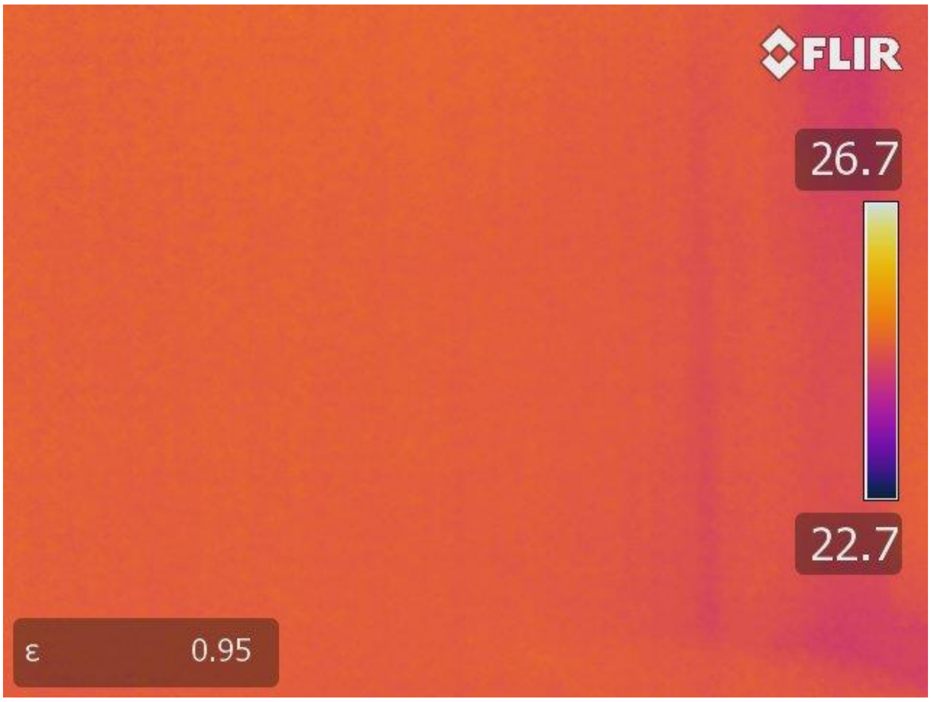


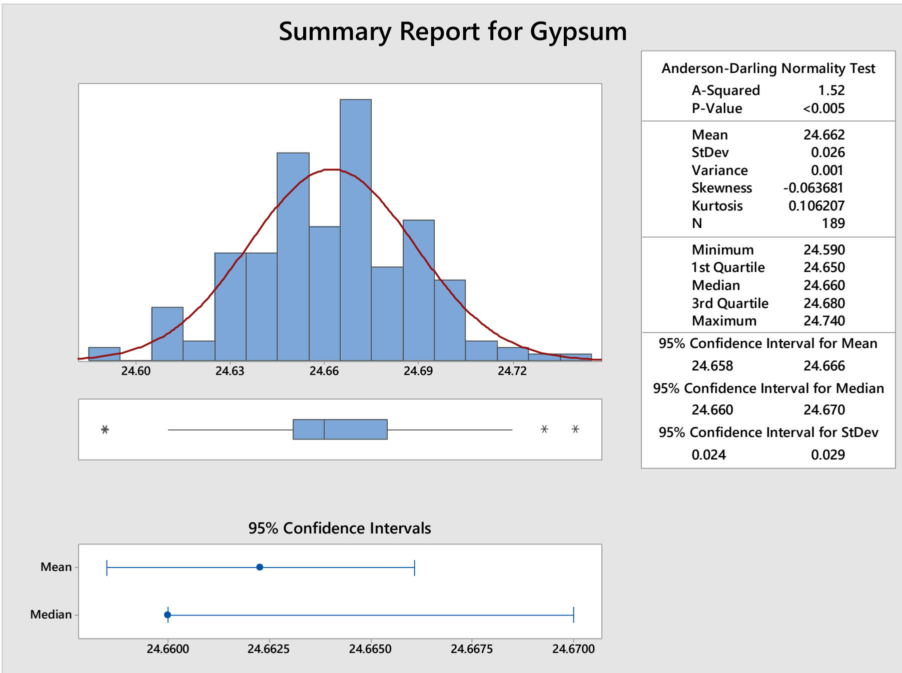
Figure 21: The image shown in Figure 20 after applying the filtering algorithm of the Python described in the previous paragraph.

4.2 Model Building

The emitted radiance matrices of the images were used to determine the material type for each wall in the image. A Monte Carlo Simulation was used in this study 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 types of materials in the interior walls images. The purpose of using the Monte Carlo Simulation was to analyze trends of the emitted radiance recorded in each image such that these values were 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 gypsum and concrete, ten samples from each material type were used in the simulation process. Figures 22 and 23 show examples of thermal infrared images of interior gypsum board and concrete walls along with their corresponding statistical characteristics summary report.

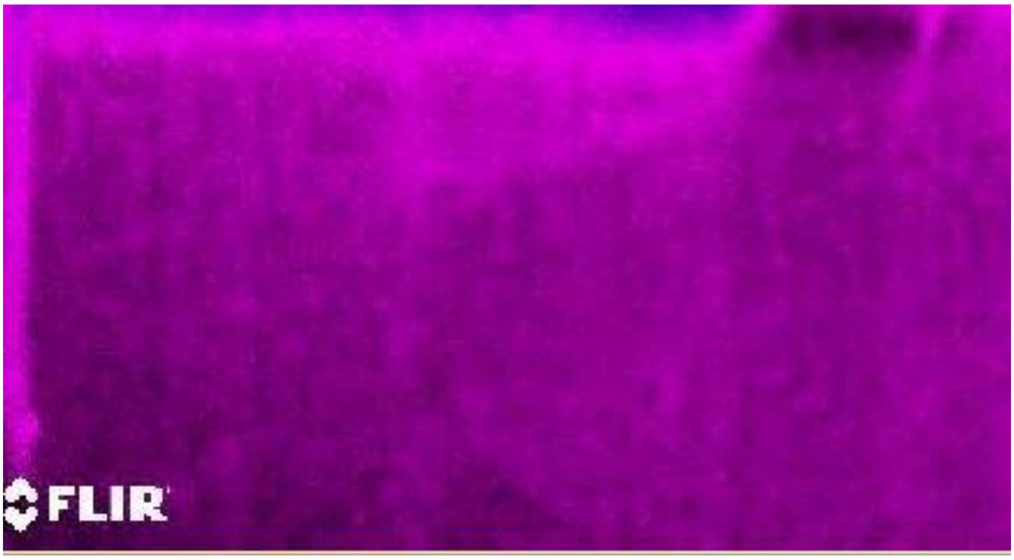


(a)

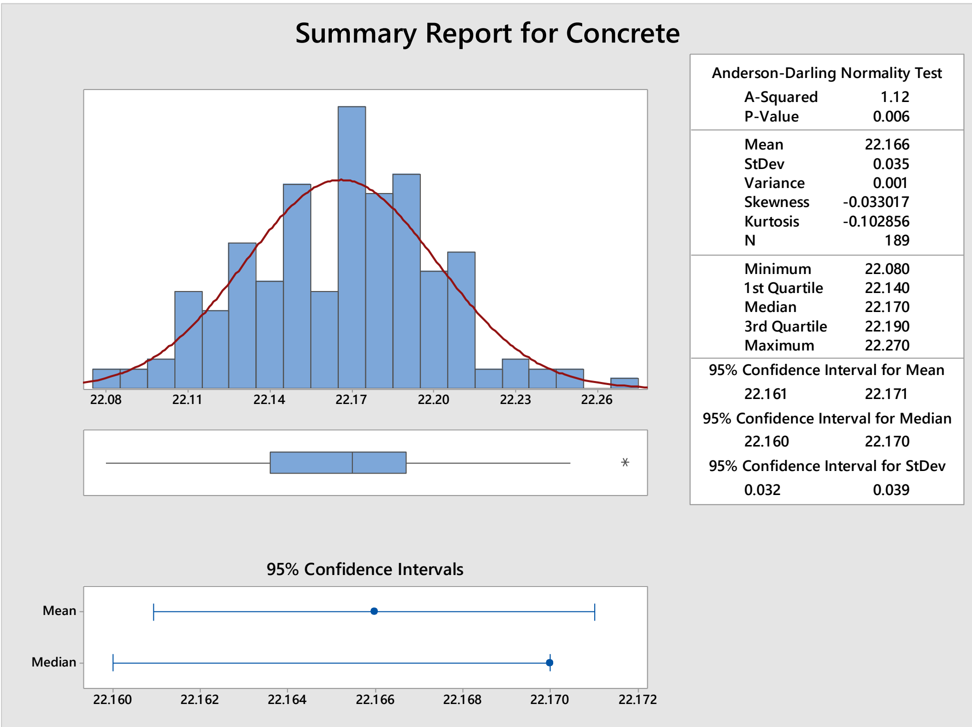


(b)

Figure 22: Interior gypsum board thermal image and the (b) corresponding statistical summary



(a)



(b)

Figure 23: (a) Concrete thermal image and the (b) corresponding statistical summary

Defects in the interior walls such as cracks, heat insulation and water leakages, and water and air infiltration, result in a change in the texture and color of the captured thermal image. Such defects would therefore be evident in the recorded emitted radiance extracted from that image. Also, the statistical data of the image (including the image histogram) would show color tone discontinuity in the area of the defect. An image or part of it, which exhibits such discontinuity would be identified and reported as "nonhomogeneous" in the Revit BIM database (Figure 30). Figure 24a shows a crack in a concrete wall, which is shown in blue color in the thermal image indicating that the crack area is colder than the rest of the wall, which is shown in red color. Also, notice that the histogram (Figure 24b) of a wall with a crack showed a discontinuity although the mean emitted thermal infrared radiation was similar to that in the histogram of the concrete wall in Figure 23b.

4.3 Integration of Texture and material information into the BIM model

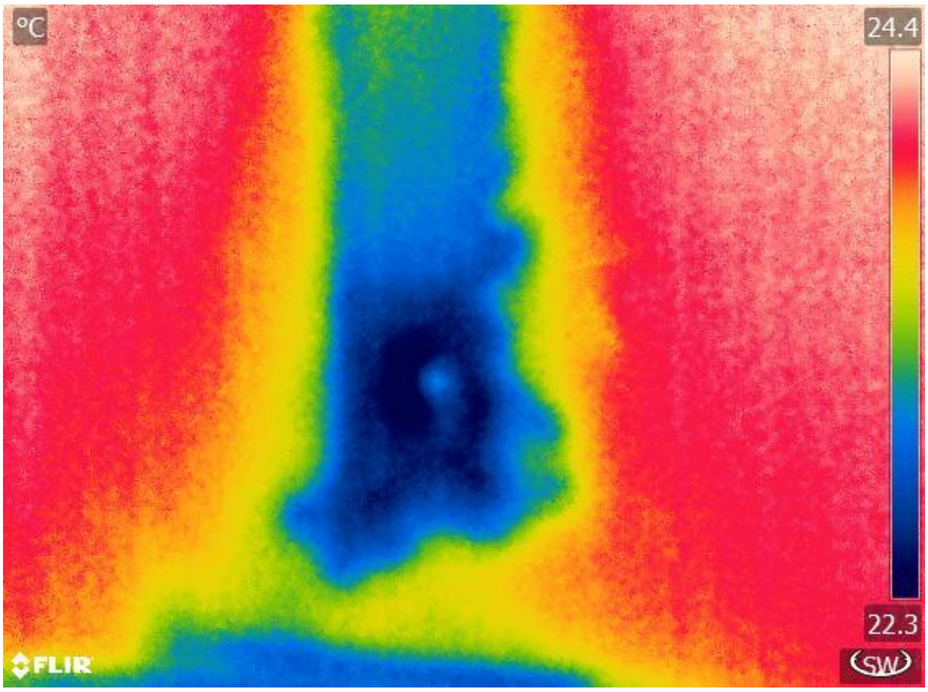
4.3.1 Gypsum wall board

Figures 25 and 26 show part of the newly created parameters unpopulated, and populated with extracted texture and material information of the interior walls, respectively.

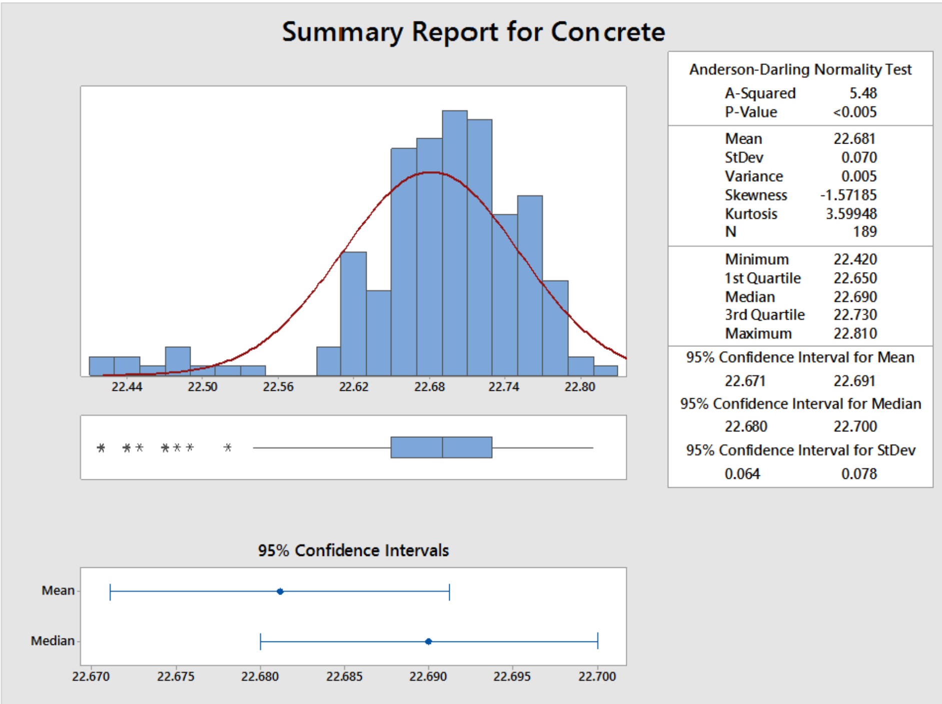
After the database was updated with the texture and material information (Figures 25 & 26), it was exported to Revit using Ideate BIMLink tool. In the Revit-based BIM model, the interior walls now have two new parameters populated with texture and the material information (Figures 27 and 28).

4.3.2 Concrete walls

Similar to the integration of the gypsum board above, the same procedure was applied for the concrete walls. However, notice that here there was a nonhomogeneous texture wall that was identified and that was reflected in the schedule of the Revit database as well as in the BIM model as shown in Figures 28, 29, and 31.

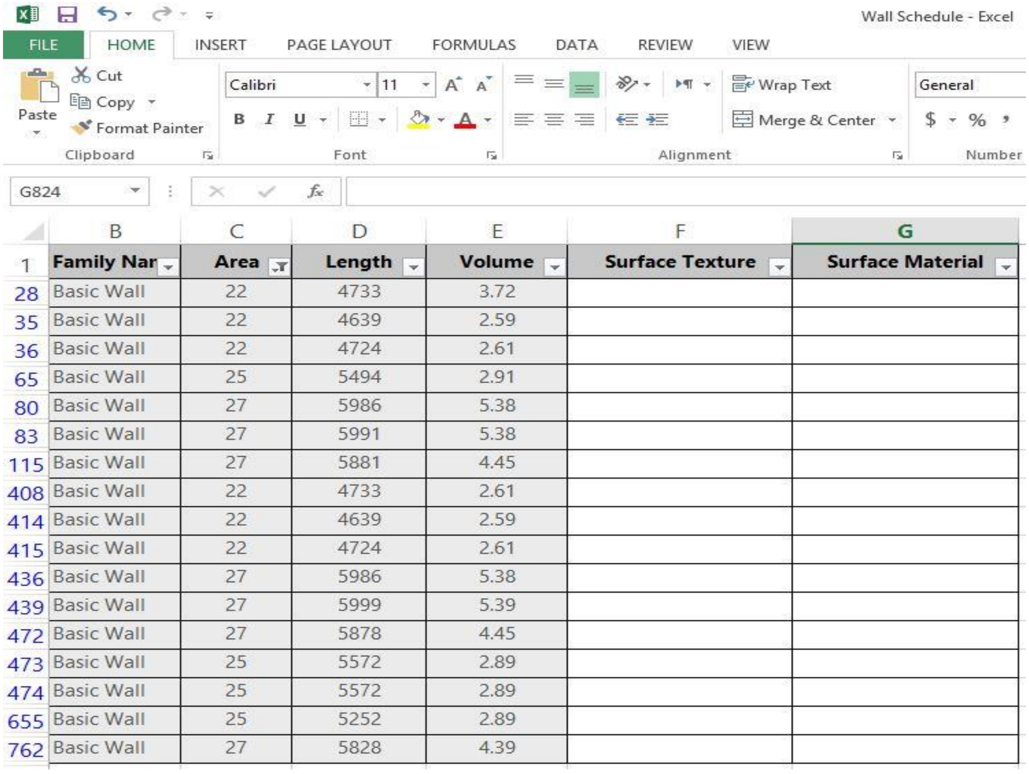


(a)



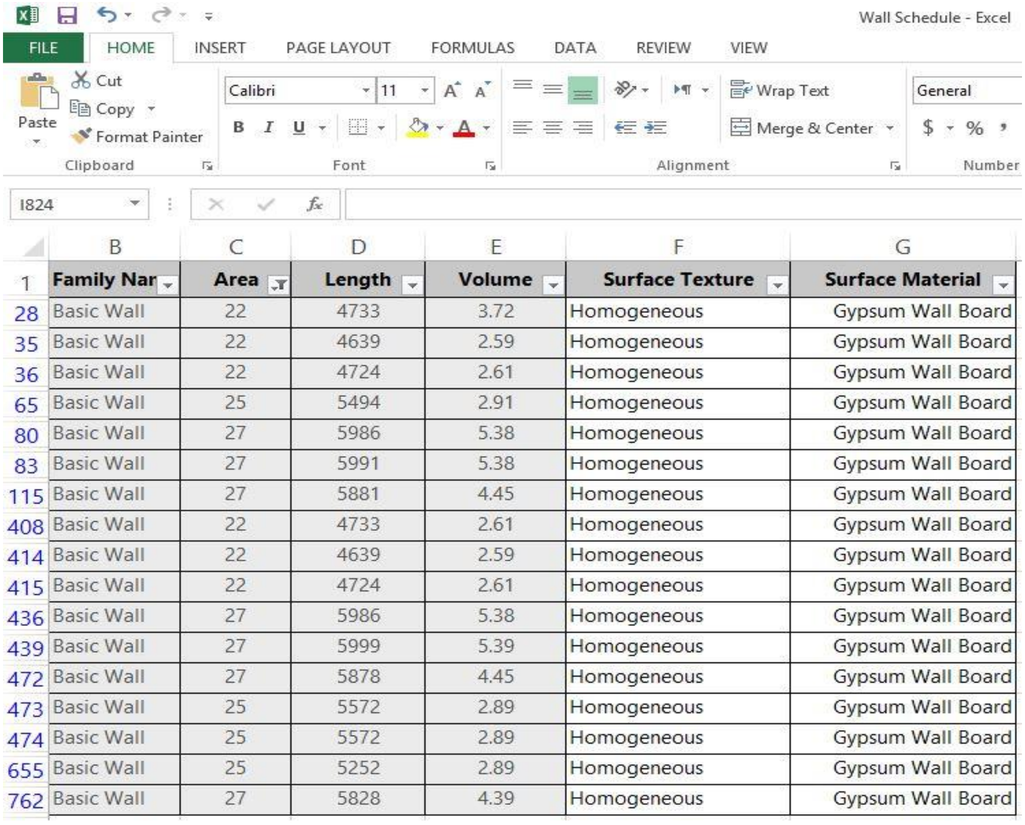
(b)

Figure 24: (a) Gypsum board thermal image and the (b) corresponding statistical summary



	B	C	D	E	F	G
1	Family Nar	Area	Length	Volume	Surface Texture	Surface Material
28	Basic Wall	22	4733	3.72		
35	Basic Wall	22	4639	2.59		
36	Basic Wall	22	4724	2.61		
65	Basic Wall	25	5494	2.91		
80	Basic Wall	27	5986	5.38		
83	Basic Wall	27	5991	5.38		
115	Basic Wall	27	5881	4.45		
408	Basic Wall	22	4733	2.61		
414	Basic Wall	22	4639	2.59		
415	Basic Wall	22	4724	2.61		
436	Basic Wall	27	5986	5.38		
439	Basic Wall	27	5999	5.39		
472	Basic Wall	27	5878	4.45		
473	Basic Wall	25	5572	2.89		
474	Basic Wall	25	5572	2.89		
655	Basic Wall	25	5252	2.89		
762	Basic Wall	27	5828	4.39		

Figure 25: Part of the newly created parameters of interior walls unpopulated with texture and material information.



	B	C	D	E	F	G
1	Family Nar	Area	Length	Volume	Surface Texture	Surface Material
28	Basic Wall	22	4733	3.72	Homogeneous	Gypsum Wall Board
35	Basic Wall	22	4639	2.59	Homogeneous	Gypsum Wall Board
36	Basic Wall	22	4724	2.61	Homogeneous	Gypsum Wall Board
65	Basic Wall	25	5494	2.91	Homogeneous	Gypsum Wall Board
80	Basic Wall	27	5986	5.38	Homogeneous	Gypsum Wall Board
83	Basic Wall	27	5991	5.38	Homogeneous	Gypsum Wall Board
115	Basic Wall	27	5881	4.45	Homogeneous	Gypsum Wall Board
408	Basic Wall	22	4733	2.61	Homogeneous	Gypsum Wall Board
414	Basic Wall	22	4639	2.59	Homogeneous	Gypsum Wall Board
415	Basic Wall	22	4724	2.61	Homogeneous	Gypsum Wall Board
436	Basic Wall	27	5986	5.38	Homogeneous	Gypsum Wall Board
439	Basic Wall	27	5999	5.39	Homogeneous	Gypsum Wall Board
472	Basic Wall	27	5878	4.45	Homogeneous	Gypsum Wall Board
473	Basic Wall	25	5572	2.89	Homogeneous	Gypsum Wall Board
474	Basic Wall	25	5572	2.89	Homogeneous	Gypsum Wall Board
655	Basic Wall	25	5252	2.89	Homogeneous	Gypsum Wall Board
762	Basic Wall	27	5828	4.39	Homogeneous	Gypsum Wall Board

Figure 26: Part of the newly created parameters of interior walls populated with texture and Gypsum Wall Board material information.

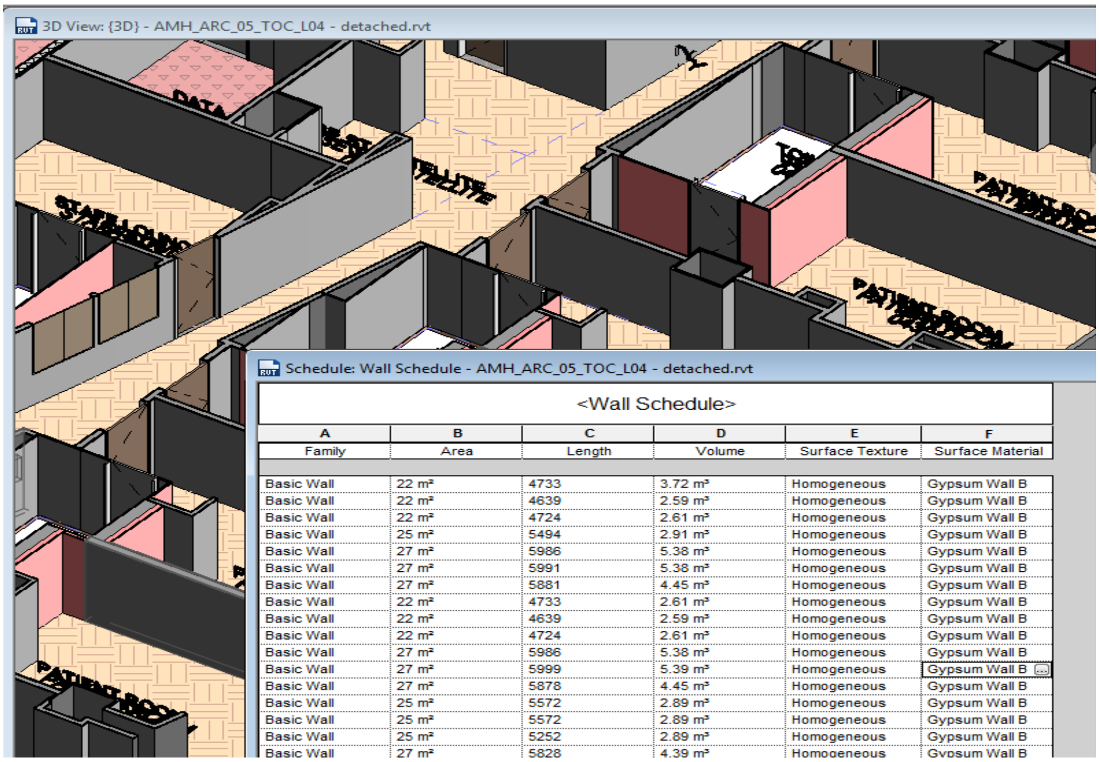


Figure 27: Gypsum Wall Board schedule in the BIM model.

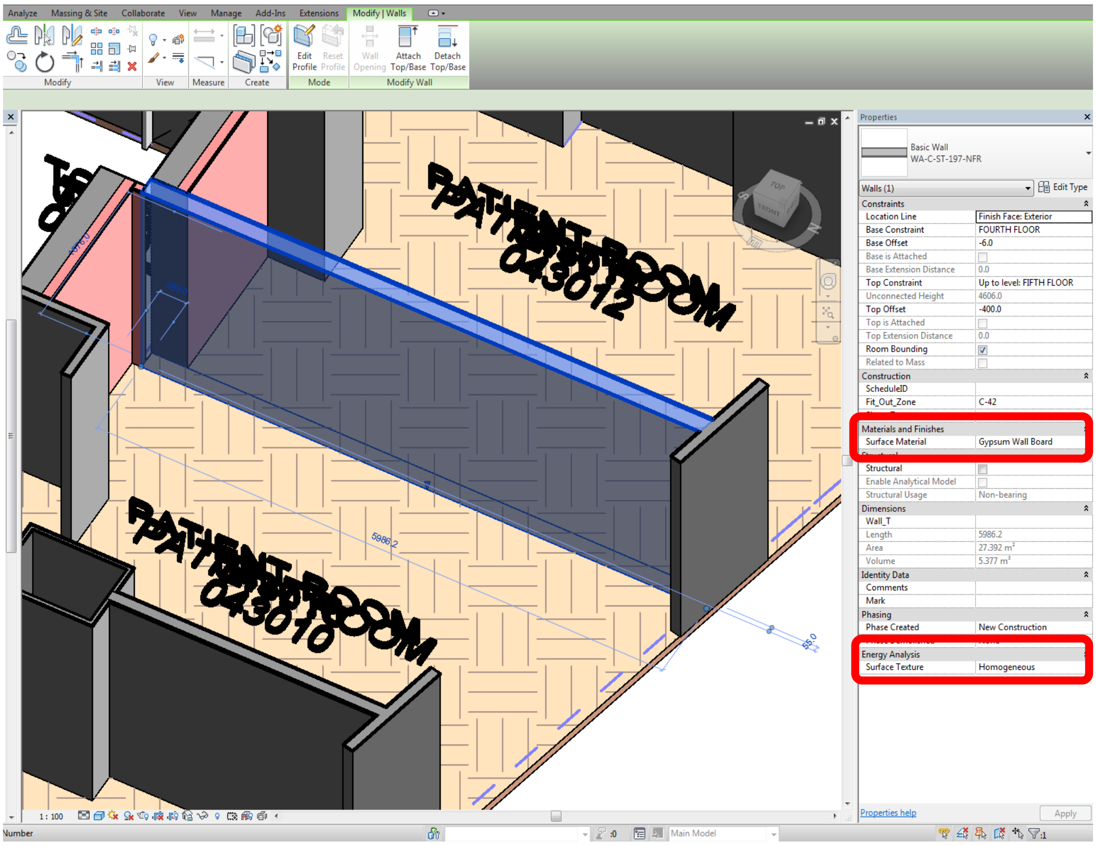


Figure 28: The updated BIM model showing Gypsum Wall Board material and homogeneous texture of the interior walls.

<Wall Schedule>

A	B	C	D	E	F
Family	Area	Length	Volume	Surface Texture	Surface Material
Basic Wall	21 m^2	2277	8.94 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	27 m^2	4450	8.14 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	24 m^2	4562	9.77 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	29 m^2	4900	8.79 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	30 m^2	4935	9.03 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	29 m^2	5500	8.74 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	33 m^2	6549	9.86 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	31 m^2	6771	9.44 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	32 m^2	6836	9.64 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	32 m^2	6900	9.52 m^3	NonHomogeous	Concrete - Cast-in-Place Concrete
Basic Wall	32 m^2	6900	9.52 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	32 m^2	7015	9.60 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	33 m^2	7673	9.89 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	27 m^2	8300	8.22 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	30 m^2	8300	8.96 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	27 m^2	8300	8.22 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	27 m^2	8300	8.22 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	27 m^2	8775	8.23 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	28 m^2	8800	8.26 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	29 m^2	9000	8.64 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	29 m^2	9000	8.59 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	29 m^2	9000	8.64 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	32 m^2	9000	9.72 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	28 m^2	9000	8.30 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	32 m^2	9000	9.72 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	29 m^2	9000	8.59 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	29 m^2	9000	8.57 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	30 m^2	9037	8.45 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	30 m^2	9300	8.93 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	32 m^2	9350	9.55 m^3	Homogeneous	Concrete - Cast-in-Place Concrete
Basic Wall	31 m^2	9350	9.26 m^3	Homogeneous	Concrete - Cast-in-Place Concrete

Figure 29: Schedule of concrete walls.

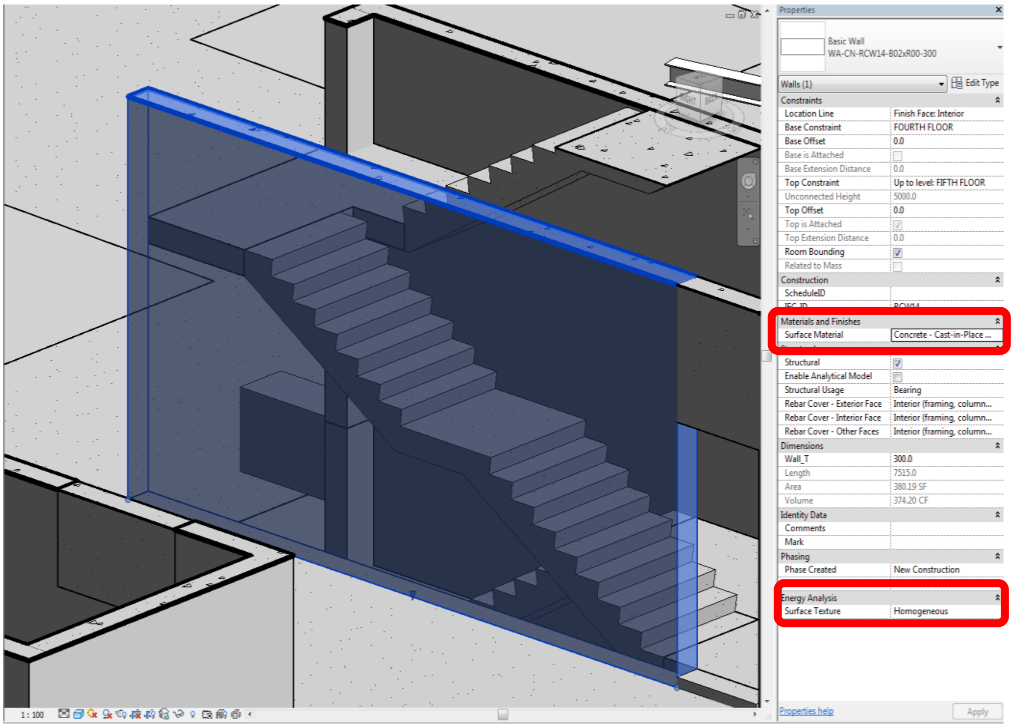


Figure 30: The updated BIM model showing concrete surface material and homogeneous texture of the interior walls.

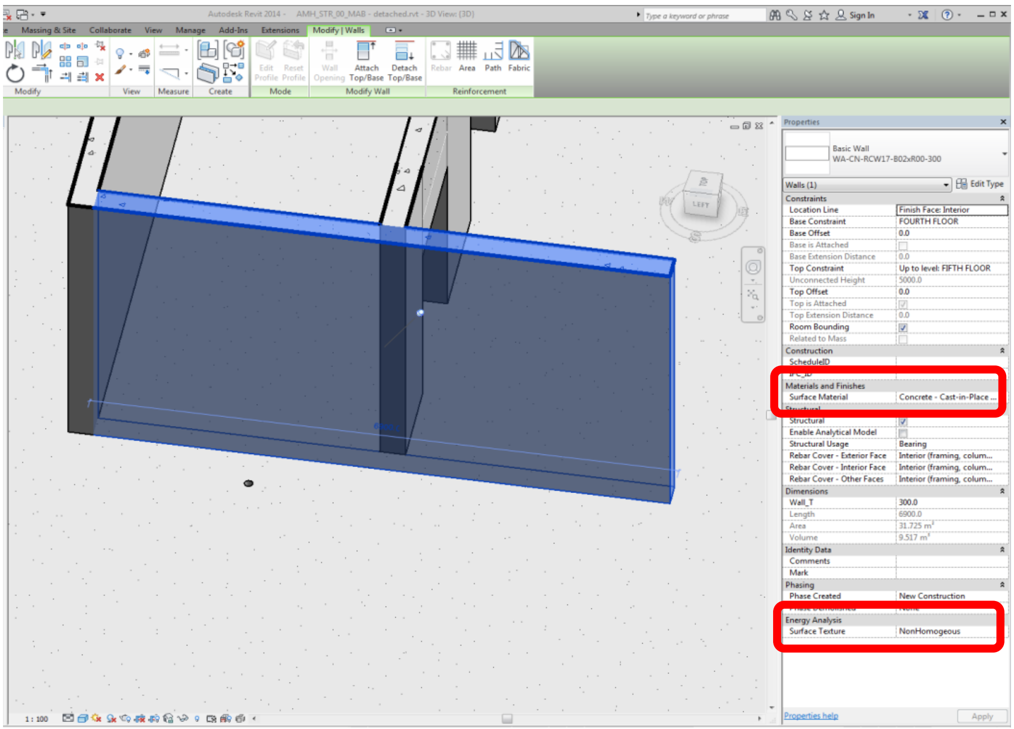


Figure 31: The updated BIM model showing concrete surface material and nonhomogeneous texture of the interior walls

Chapter 5: Conclusions and Recommendations

5.1 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 better communicate the as-is building conditions to the owners. To achieve this goal, this study presented a method for extracting material and texture information of the interior walls of the fourth floor in tower C in Mafraq Hospital, Abu Dhabi, UAE using infrared remote sensing and integrating the new information into the Revit-based BIM model database of the hospital. The updated BIM database would provide means to auditors and maintenance engineers to query the database and extract information about texture and surface materials of the interior walls. This would allow practitioners to accurately identify potential problems given the homogeneity of the texture and/or material on a wall.

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 resultant thermal images of the interior walls were then converted into emitted thermal infrared radiance at each pixel using software that comes with the camera. A statistical analysis approach of the emitted radiance distribution based on Monte Carlo simulation was used in order to identify interior walls materials (interior gypsum board or concrete). Following this analysis, a relationship between the mean value and standard deviation of the radiance values was developed and used to identify the two material types in the rest of images. Surface texture and material information were then integrated into the database of the Revit-based BIM model of the hospital. With texture and material information integrated into the model, one can identify nonhomogeneous textured wall patterns and further identify potential problems such as heat loss or water leakage. Moreover, the method developed in this study will help energy auditors to save the time they normally spend on analyzing large numbers of unorganized thermal images provided by site technicians, and instead focus on the sources of the problems and examine various retrofit alternatives.

5.2 Recommendations

While the current study has successfully utilized infrared thermal sensing to extract textural and material information of two common material types of interior walls and integrated that into the BIM model, it would be advantageous to utilize multispectral sensing to acquire the images of building elements in future studies. Such images will help in identifying texture and material types of larger dataset of different materials of building elements such as floors, columns, doors, windows, etc. Then, having unsupervised classification algorithms developed for remote sensing imagery can provide an important resource for classifying these multispectral images of the building elements.

The use of the proposed methodology is further recommended on a regular basis throughout the life cycle of the building. This way, the regularly collected texture and material information of building elements would provide a rich up-to-date BIM database, which would make comprehensive energy auditing and robust water leaks detection possible. Given that this study has provided a framework for extracting textural and material information and integrating that into the BIM model database, developing a method that can help in identifying the exact locations of the defects, heat losses, or water leaks in the interior walls would certainly be valuable to the discipline.

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Appendix I

This code was developed in Python and was used to segment and extract texture features of internal walls of Mafraq Hospital for the purpose of this project.

```
######### Importing the necessary libraries
# PIL/Skimage library: contains functions for importing images and filtering functions
# Numpy library: contains numerical functions
from PIL import Image,ImageFilter
from skimage import measure
import matplotlib.pyplot as plt
import numpy as np

# Choose working directory
%cd 'D:\OneDrive\Baha\Research\Data'

# Import image into image_thesis then convert it into array in image_thesis_array
image_thesis = Image.open('xx.jpg')
image_thesis_array = np.array(image_thesis)
image_thesis_array = image_thesis_array[:,:,0]

# Image analysis
contours = measure.find_contours(image_thesis_array, 5)
fig, ax = plt.subplots()
ax.imshow(image_thesis, interpolation='nearest', cmap=plt.cm.Paired)

for n, contour in enumerate(contours):
   ax.plot(contour[:, 1], contour[:, 0], linewidth=2)

# Plot Results
ax.axis('image')
ax.set_xticks([])
ax.set_yticks([])
plt.show()
```

Vita

Asem Ahmad Zabin was born on September 23, 1990 in Sanaa, Yemen. After completing his high school in 2008, he was granted a Merit Scholarship from the American University of Sharjah (AUS) to join the Civil Engineering bachelor program, from which he was graduated in 2012 with minor in Engineering Management. Soon after graduating he received a graduate teaching assistantship from AUS to join the Civil Engineering Masters program.

Mr. Zabin is currently working as a BIM engineer at iTech Management Consultancy and is also member of the American Society of Civil Engineers (ASCE). His research interests include Building Information Modeling (BIM), Virtual Project Delivery (VPD), Geographic Information Systems (GIS), and Project Management.