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Automated 3D model reconstruction to support energy-efficiency

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Abstract

There is a need for diagnostic methods to detect and retrofit energy leakages in order to reduce the energy consumed for heating and cooling. This paper proposes a method to map the infrared thermography into 3D point cloud acquired against the desired location. The mapping result shows that the proposed method can map the infrared thermography onto the 3D point cloud acquired at a different location and at any time without the setup of hardware and equipment.

Keywords: 3D thermal model, energy-efficiency, thermography, laser scanned data

1 Introduction

The energy consumption of buildings in the United States accounts for 41% of total energy consumption based on 2009 statistics [1]. This energy consumption is projected to steadily increase due to people's desire to improve their quality of life [2], and buildings are predicted to reach 42% of total energy consumption by 2053 [1]. Heating and cooling systems are responsible for almost 80% of the energy consumption of buildings [3]. A large portion of this consumption is used to maintain the internal temperature by heating or cooling [4]. Thus, there is a need for diagnostic methods to detect and retrofit energy leakages in order to reduce the energy consumed for heating and cooling.

Currently, many non-destructive testing methods, such as an air leakage test, a co-heating test, infrared thermography, heat flux measurements, and others, are applied to detect the areas where energy leakage occurs [5, 6, 7]. Among the non-destructive testing methods, an infrared thermal camera is the widely used preliminary investigation tool because it does not cause physical damage during the exploratory investigation. This camera also

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performs quickly and does not incur costly expenses [6, 8]. The U.S Department of Energy (DOE) estimated that the energy diagnosis of a building using infrared thermography could reduce energy consumption from 5% to 30% [9].

The ISO standard 6781-1983 is most commonly used standards for conducting building energy diagnostics [10] and 14 member bodies approved the standard (Australia, Austria, Belgium, Canada, Denmark, Egypt, Finland, France, Italy, Japan, Norway, Spain, Sweden and the USA) since 1982 [11]. The ISO standard 6781-1983 outlines the general procedure for the interpretation of infrared thermography [12]. First, after acquiring the infrared thermography of a location exhibiting anomalies or is of special interest, the location is marked on the blueprint. Second, the anticipated temperature distribution is determined by using the properties of the materials, like emissivity, which is evaluated based on the blueprints related to the building and other construction documents. External conditions, such as outdoor air temperature, should also be included. Third, heat anomalies are defined by comparing the anticipated temperature distribution and the actual temperature distribution. For example, the large temperature variations with irregular shapes that are visible at the joints and junctions may be defined as air leakage.

Similarly, the diagnosis of a building by using infrared thermography requires not only the blueprints but also the property information of the materials and data on the joints and junctions of the components. Because most of the blueprints are not digitalized, the experts should manually check the floor plan, elevation, detailed blueprints and other documentation on every material. Then the data are gathered, including external information such as the emissivity table. However, considering the multitude of infrared thermography acquired from a building and the number of relevant blueprints, manually performing all analysis is too labor-intensive and time-consuming. Besides, in the case of lost blueprints, obtaining the information on the properties of materials needed for the analysis of infrared thermography may be difficult. In such cases, the calculation of information on the properties of materials such as the U-value is also needed, but manually calculating the properties of materials by each component will be challenging. Hence, a method to map the infrared thermography to the building information model is necessary and must include the blueprint, information of properties of materials, and joints and junctions of the components.

Earlier studies tried to automatically map the infrared thermography on three-dimensional (3D) point cloud [13, 14, 15, 16, 17]. However, the first problem is that the infrared thermography and 3D point cloud data have to be acquired at the same time and at the same location (see, for example, [15, 17]). Acquiring the 3D point cloud to match against the building whose physical appearance remains unchanged every time its energy is diagnosed could be considered as collecting unnecessary data. Assuming that it takes 10 minutes to scan once, acquiring the 3D point cloud data every time the infrared thermography is acquired is a waste of time. Hence, this method limits the merits of infrared thermography, as data can be acquired quickly in camera form. Second, because the junction of vertical and horizontal lines in the building is used as its feature point when mapping the infrared thermography on the 3D point cloud data (see, for example, [16]), a problem still remains: the acquired infrared thermography, including its feature point, is inadequate in the detection of thermal patterns. To acquire the infrared thermography with a resolution adequate for the detection of thermal patterns, infrared thermography should be acquired within eight meters [18]. However, the detection of thermal patterns using acquired infrared thermography may be difficult because to acquire the infrared thermography of the façade of the building, it needs to be shot from a considerable distance due to the narrow field of view of the infrared camera. Thus, a method of acquiring the infrared thermography of the desired area at the desired time and mapping with 3D point cloud data needs to be proposed.

This paper proposes a method to map the infrared thermography into 3D point cloud acquired against the desired location at any time without the setup of hardware and equipment to acquire both the infrared thermography and 3D point cloud.

2 Overview of the proposed 3D thermal modelling framework

2.1 Acquisition systems

This research used an infrared thermal camera equipped with a built-in lens to acquire infrared thermography and visible images at the same time. The infrared thermal camera with a built-in lens is commercially available from an infrared thermal camera manufacturer and can help users understand and document the image acquired by infrared thermography. To provide both infrared thermography and a visible image at once, the fields of view of

both the infrared thermal camera and visible camera are the same. Furthermore, the option to acquire infrared thermography and a visible image simultaneously is possible because the geometric relationship between the infrared thermal camera and the visible camera is measured prior to data acquisition.

To obtain a colored 3D point cloud, a laser scanner equipped with an internal camera is used. This device is commercially available from a laser scanner manufacturer to provide a 3D point cloud automatically mapped with color. To get the colored 3D point cloud, the correspondence between the 3D point clouds and the pixels of the color image acquired by the internal camera is defined prior to data acquisition, and the option to acquire colored 3D point cloud is included.

2.2 Offline construction of image database

The laser scanner used in this research acquires the color of each 3D point cloud in addition to spatial information. The database image is generated using the color of the 3D point cloud. To set the origin of the image plane, the internal camera parameter and position of the image acquisition are determined. Set in advance, the calibration of the visible camera equipped with an infrared thermal camera is performed to calculate the internal camera parameter. The position of the image acquisition is then determined by dividing the façade of the building by a certain number, such as 2 by 5 grids. Based on the internal parameter and the divided region, the distance and angle between the façade of the building and the position of the image are identified. The height and width of the image are defined by the resolution of visible camera. The database image is generated with the same resolution as the visible image acquired through the infrared thermal camera (Figure. 1). After the origin of the image plane is set, the transformation matrix for the projection of the 3D point cloud onto the image plane is calculated. Then the 3D point cloud is substituted by the projection transformation matrix on the image plane. The color of the pixel on the image plane is determined by the color of the nearest 3D point cloud projected on the image plane. This process is repeated until the database image is generated for the entire position of image.

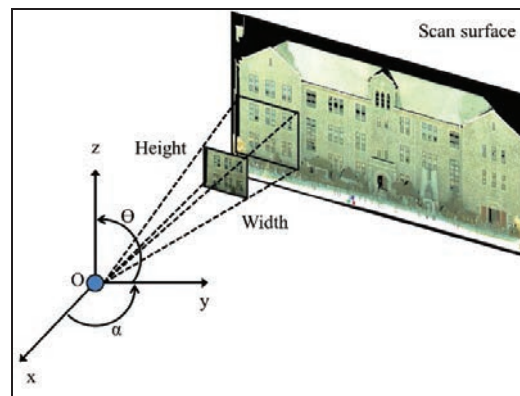


Figure 1. The generation of database images from 3D point clouds

2.3 Pre-processing

The distortion of the digital lens within the infrared thermal camera could be the cause of inaccurate results of matching the features extracted from the visible image to the database image. A distortion correction of the visible image is performed to match the features between the visible image and database image. Figure. 2(a) is the visible image acquired by infrared thermography and Figure. 2(c) is the database image. In this case, the infrared thermography and 3D point cloud are acquired at two different times, depending on the objective of the research, which exposes the visible and database images to different illumination effects. To solve the problem caused by the effects of different illumination, color space transformation and histogram equalization are performed. The YIQ

color space known as the color space invariant to illumination is used for the color space transformation [19]. Moreover, the histogram equalization method that can reduce the effect of illumination is applied [20].

First, the distorted visible image acquired using the infrared thermal camera is corrected based on the internal parameter calibrated prior to data acquisition. Afterwards, the color space of the corrected visible image is transformed from RGB to a YIQ color space. Among these, the grayscale image is generated with a Y component. Then, the histogram equalization is applied. Figure. 2(b) and (d) show both visible and database images that have undergone pre-processing.

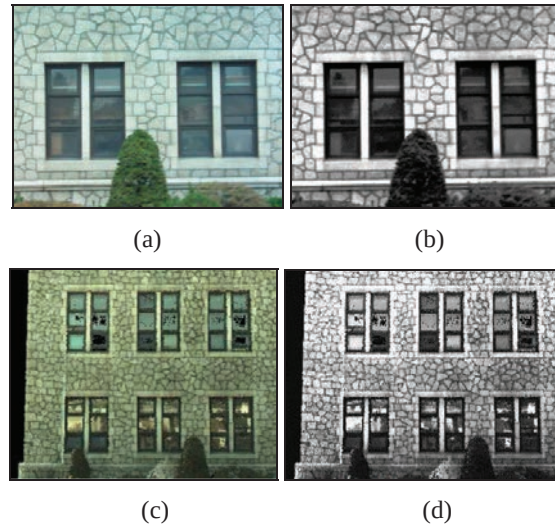


Figure 2. (a) visible image, (b) pre-processed visible image, (c) database image, (d) pre-processed database image

2.4 Feature extraction and matching

In this research, the SIFT, proposed by Lowe [21], is applied to match the database image and visible image. The database image is generated through the same internal parameter of the camera as the visible image. Moreover, the database image is generated including a wide region such that it could already cover the region acquired with infrared thermography. At this time, the transformations that might occur between the database image and the visible image are rotation, translation, and zoom transformation. It has been found in various studies that SIFT is invariant to be changed by rotation, translation, and scale [22].

SIFT consists of four steps, namely scale-space peak selection, feature points localization, orientation assignment, and feature point descriptor. The first step detects the potential keypoints at diverse positions and scales. For this, the Gaussian pyramid is constructed and the local extrema is detected at Difference of Gaussian (DoG) image. After the potential keypoints are found, in the second step the keypoints with low contrast are identified and removed from the rest of potential keypoints. Next, the orientation of each keypoint is defined based on the gradient orientation of images. Lastly, the local image patch is divided into 4-by-4 sub-blocks around the keypoints. After building the histogram on the gradient orientation and the magnitude of pixels of each sub-block, a 128-dimensional vector is generated by connecting the bin values of the histogram in series.

2.5 Matching refinement

After matching the keypoints between the visible image and database image, the matched keypoints are then used to compute the transformation matrix to align the visible image with the database image. Although the SIFT is highly distinctive, a pair of mismatched keypoints may still exist [23]. The pair must be removed because it may affect the transformation matrix. In this research, the RANSAC algorithm, using homography as the geometric constraint model, is applied to remove the pair of mismatched keypoints. Homography is applied to the two images in case translation, 3D rotation (roll, pitch, and yaw), and zoom transformation occur [24]. When translation, rotation, and zoom transformation happen in both the visible image and the database image acquired through infrared thermal camera, homography becomes the most suitable transformation for the geometric constraint model.

The matching refinement applied with homography-based RANSAC is performed as demonstrated in the following process. First is the random selection of four pairs among the pairs of matched keypoints. Using the selected four pairs, the homography is computed. After transforming the homography, the sum of the squared difference between the matched keypoints is calculated and the inlier of the pair below threshold value is determined. The set that includes the largest inlier is identified as well, and the homography of all inliers is calculated. Afterward, the matching correctness of the calculated homography is computed. If the matching correctness is high, end the process; otherwise, repeat the entire process. Figure 3 shows the result of applying homography-based RANSAC.

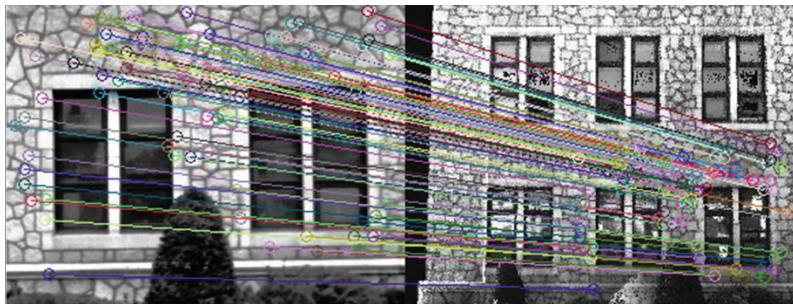


Figure 3. Feature matching results

2.6 Image matching

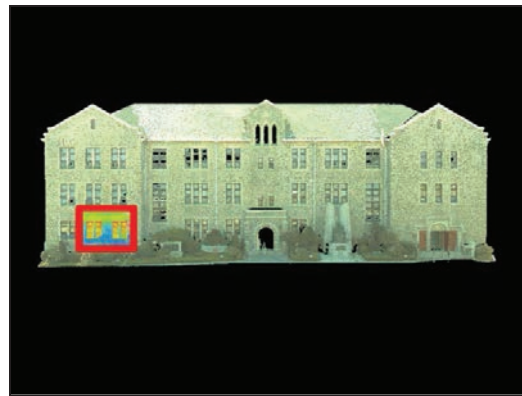
This research proposes a method for measuring image similarity based on the number of matched keypoints with the following. Because the database image is generated by dividing the façade of the building, there is only one piece of the database image that includes a visible image. Once the mismatched features are removed, a large number of matched keypoints exist for the image of the same object, whereas only a very few number of matched keypoints exist for the image of the other object.

With regard to the one piece of visible image, matching refinement for all images in the database is performed. Afterward, the number of pairs of matched keypoints in all images in the database is calculated. The database image with the greatest number of keypoint pairs is selected as the image most similar to the visible image.

2.7 Data mapping

After finding the best transformation matrix through RANSAC, the infrared thermography can then be mapped on the 3D point cloud. Because the fields of view of infrared thermography and the visible image are the same, the region of infrared thermography can be confirmed within the database image by applying the transformation matrix

of the visible image and database image on the infrared thermography. Then, the infrared thermography is projected on a three-dimensional coordinate. The thermal data of the pixel corresponding to the 3D point cloud that exists within the pixel of infrared thermography on the three-dimensional coordinate is mapped. Figure 6 shows the result of mapping the infrared thermography on a 3-D point cloud.



(a)



(b)

Figure. 6. (a) infrared thermography mapping result (b) magnified portion of (a)

3 Conclusion

This paper proposes a method for mapping the infrared thermography onto a 3D point cloud acquired at a different location and at any time without the setup of hardware and equipment. Infrared thermography was acquired by using an infrared thermal camera equipped with a built-in lens, and the 3D point cloud was acquired by using a laser scanner equipped with an internal camera. The pre-processing is proposed to extract features between the visible image and the database image acquired at different times. Then, a feature extraction and matching refinement method according to the transformation between the visible image and database image is used to calculate homography. The mapping result shows that the proposed method can map the infrared thermography onto the 3D point cloud acquired at a different location and at any time without the setup of hardware and equipment. Future research will focus on evaluating the performance of the proposed method.

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