Building element recognition with thermal-mapped point clouds

Pileun Kim[a], Jingdao Chen[b], and Yong Kwon Cho[a]

[a] School of Civil and Environmental Engineering, Georgia Institute of Technology
[b] School of Electrical and Computer Engineering, Robotics Institute, Georgia Institute of Technology
E-mail: pkim45@gatech.edu, jchen490@gatech.edu, yong.cho@ce.gatech.edu

Abstract –

Automated recognition of building elements convey vital information for inspection, monitoring and maintenance operations in indoor environments. However, existing object recognition methods from point clouds suffer from problems due to sensor noise, occlusion and clutter, which are prevalent in indoor environments. This paper proposes an object recognition method based on thermal-mapped point clouds for building elements consisting of electrical systems and heating, ventilation, and air-conditioning (HVAC) components. The proposed processing pipeline involves data collection from a mobile robot using both laser scanners and a thermal camera where temperature mapping can be performed from thermal images to point cloud. Next, the ceiling region containing the building elements of interest is identified and extracted from the point cloud. Segmentation of peak and valley thermal intensity regions is carried out based on absolute and relative temperature threshold values. The identified point cloud clusters can be each associated with a building element and localized based on the cluster center. The proposed building element recognition method was validated with two sets of laser scan data collected in an indoor laboratory. Experimental results for detection of lighting elements and cooling elements showed that the method achieved an average of 100% precision, 90% recall, and 0.25m root mean squared error (RMSE).

Keywords –

Laser scanning; Point cloud; Object recognition; Thermal image

1 Introduction

Laser scanned data in the form of 3D point clouds has emerged in recent years as one of the primary methods of data collection from built environments as well as construction sites. Due to the large number of possible applications, laser scanning technology has rapidly improved in terms of scanning speed and accuracy [1]. 3D point clouds are advantageous because they contain valuable geometric information at a high resolution that can be used to perform semantic modelling [2], quality assessment [3], defect analysis [4], and asset management [5].

Researchers in the field have explored various ways to automatically recognize building elements from unstructured point cloud data in order to reduce the manual effort required to annotate and label the point clouds. Examples of building elements that can be recognized are walls, ceilings, floors, doors, windows, and roofs [2][6]. In particular, recognition of planar structures such as walls and floors is a key component of robotic mapping of indoor environments [7]. Recognition of building elements is also highly relevant for Building Information Modelling (BIM) applications, which involve the creation of a BIM model representing the shape, identity, and relationships of scanned objects [8][9][10]. However, point cloud data is often collected at a high volume which imposes high memory and processing requirements for automated point cloud processing algorithms due to the large number of points involved [11]. In addition, raw point cloud data collected from indoor environments is also known to suffer from sensor noise, occlusion, and clutter [12].

In short, the requirement for automatic object recognition methods is increasing by using robots deployed in field operations. To address the need for more sophisticated building element recognition methods from point clouds, this study proposes a method using a combination of thermal images and laser-scanned point cloud to detect and localize electrical systems and heating, ventilation, and air-conditioning (HVAC) components. In general, the thermal information provides many advantages because people can be detected easily both indoor and outdoor environments. Also, the point cloud offers 3D geometric data. Therefore, the 3d point cloud with thermal data can observe a sort of concealed objects such as heating pipes as well as structural properties such as defects. The method relies on the heat signature emitted by these building elements to accurately extract and identify the building elements from a thermal-mapped point cloud. This is because regions in the point cloud with high thermal intensity can be attributed to lighting elements whereas regions with low thermal intensity can be attributed to cooling elements. The following sections will present an overview of the related work, methodology, results, discussion, and conclusion.

2 Related Work

Recognition of building elements from a job site can be performed through various different mediums such as visual images [13][14][15][16], thermal images [17], [18], and laser-scanned point clouds [2][6]. Each sensory medium has its own advantages and disadvantages when applied to the task of object recognition. For example, 2D-based sensing is vulnerable to changes in view angle, lighting conditions, as well as cases with multiple occluding objects [19]. On the other hand, 3D-based sensing requires a computationally intensive registration step to combine scan data [20] and is also subject to clutter and point density variations [21]. The following subsections summarize the common techniques that are used for object recognition from point clouds and thermal images respectively.

2.1 Object recognition from point clouds

Object recognition methods from point clouds rely on geometric information from point samples to infer semantic properties of the unknown object. For objects that exhibit primitive shapes such as walls and floors, simple geometric reasoning can be used to identify these components in a point cloud [2], [6]. For objects that exhibit complex geometry, one possible method is to use a lower dimensional feature representation of the point cloud in a vector form known as a descriptor [22]. A 3D descriptor can be calculated based on histograms of orientations [23], curvatures [24], or length and area statistics [25]. Additionally, when a computer-aided design (CAD) model of the target object is available, object recognition can be performed by directly registering the CAD model with the point cloud object and examining the registration error [11]. Alternatively, the 3D data can be projected into a 2D form to take advantage of existing 2D recognition algorithms [26].

2.2 Object recognition from thermal images

There are various methods for recognizing objects from a thermal image. Treptow et al. [27] used an elliptical model with particle filter to identify the contours of a person from the thermal images. This method shows that accurate detection at high frame rates, but it only works for one person with the highest measurement probability. Similarly, Socolinsky et al. [28] revealed that performing facial recognition by using thermal image is more accurate than visual image because of high invariance to illumination condition. However, these studies focused on 2D thermal imaging for the small objects and did not consider global perception at the entire space. To solve the problem of detecting multiple objects from a single image, Davis et al. [29] used the technique of contour enhancement. This technology successfully detects multiple objects on a thermal image over a wide range of environmental conditions. It is also robust with respect to object shape and can extract silhouettes such as people, dogs and vehicles. However, it only generates an overview of the detected objects and does not explicitly indicate the meaning of each object. To detect building elements, Balaras and Argiriou [30] used thermal infrared imaging for inspecting of building elements. Also, Freitas et al. [31] used infrared thermography for a rapid non-destructive diagnosis of building envelopes. However, their work only 2D thermal images so that it might be easy to detect where energy leaks and perform diagnotics, but difficult to identify the shape for object recognition.

3 Methodology

The task of recognizing building elements from thermal-mapped point clouds can be divided into three steps: (i) collect data from a mobile robot, (ii) perform thermal mapping for the point cloud data, and (iii) perform recognition of building elements. Each step will be described in detail in the subsections below:

3.1 Data collection from a mobile robot

A robotic system, as shown in Figure 1, is used to acquire map information from the environment in the form of point cloud data as well as thermal images. The robotic system consists of a hybrid scanning framework with 4 units of SICK laser scanners [32] and one thermal camera (640 x 480 pixels) [33] mounted on a rotating body. The laser scanners used are line laser scanners with a horizontal resolution of 0.072 degrees and a vertical resolution of 0.167 degrees. It performed scans 150º horizontally and 190º vertically. Therefore, the total number of collected points was around 1,000,000. The infrared camera is able to capture 25 degrees in the horizontal direction and 18 degrees in the vertical direction at a time; therefore, at least six panning movements are required to cover 150 degrees. In this experiment, three tilting movement are applied to cover 54 degrees vertically.

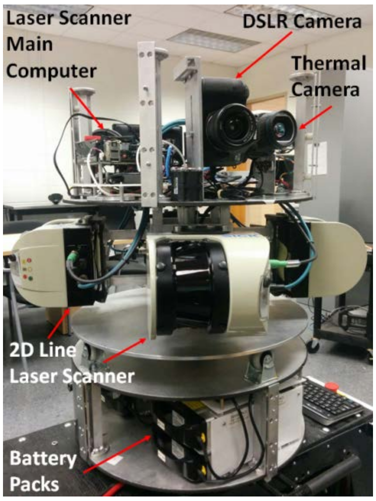


Figure 1: Sensor setup for the robotic system

3.2 Thermal mapping for point cloud data

The following subsection describes how to combine the acquired point cloud data with thermal images. The process works by mapping each 3D point in the point cloud, (x, y, z) to 2D homogenous image coordinates (u, v, w) in thermal images and extracting the temperature information from that pixel location (Equation 1). The camera extrinsic matrix, which contains a rotation term, R and a translation term, T, maps 3D points from the world coordinate frame to the camera coordinate frame. This matrix can be determined by the position and orientation of the thermal camera when each thermal image is captured. On the other hand, the camera intrinsic matrix, K, describes the mapping between 3D points in camera coordinates to 2D points in image coordinates. This matrix is shown in Equation 2, where f_x and f_y are the focal lengths in the x and y axes whereas (c_x, c_y) is the image center. The values of these parameters can be obtained by a camera calibration process.

$$\begin{bmatrix} u \\ v \\ w \end{bmatrix} = K\,[R\ \mid t] \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \tag{1}$$

$$K = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \tag{2}$$

The panoramic view of the laser scanned point cloud can be created directly using the angular coordinates of each point. Equation 3 parameterizes the mapping from the points of 3D camera coordinates (u, v, w) to its corresponding points on the panoramic view (x, y) where x, y are the image coordinates of the projected point cloud.

$$\begin{aligned} x &= \frac{1}{\Delta\theta}\tan^{-1}\frac{v}{w} \\ y &= \frac{1}{\Delta\theta}\tan^{-1}\frac{w}{\sqrt{u^2+v^2}} \end{aligned} \tag{3}$$

3.3 Recognition of building elements

After a thermal-mapped point cloud is acquired, building elements of interest can be detected and localized from the point cloud. First, the point cloud is subdivided into different subsections based on the z-value, which is the height. The subsection with the largest z-value, which represents the ceiling region, is extracted from the point cloud. An example of such an extracted subsection is shown in Figure 2.

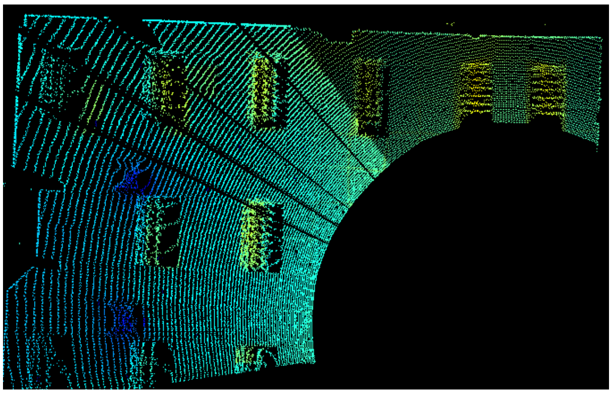
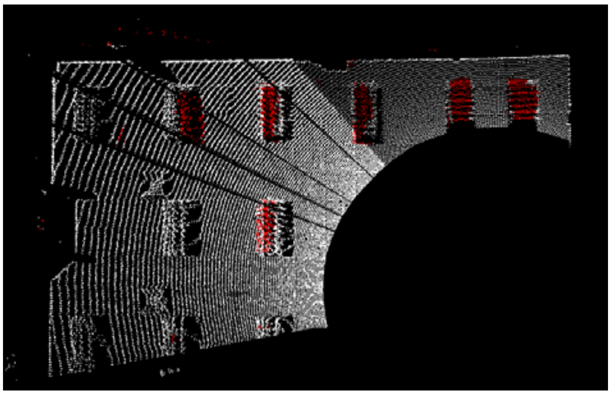
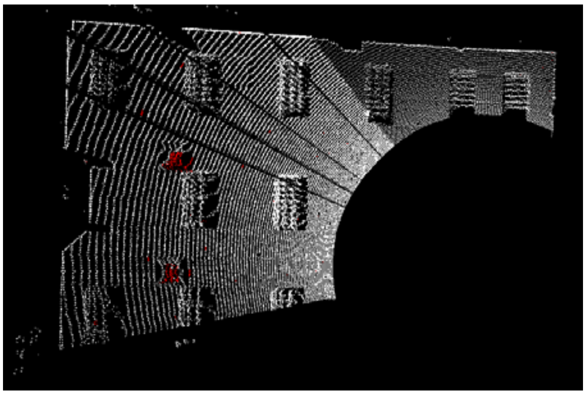


Figure 2: Subsection of a building point cloud consisting of the ceiling region

Next, the thermal information contained in the point cloud is used to identify heat-emitting objects, which in this case are lighting elements, as well as heat-absorbing objects, which in this case are cooling elements. The main idea is to identify regions in the point cloud which constitutes peaks (high intensity) or valleys (low intensity) in terms of the temperature. This is achieved by using a combination of absolute thresholds and relative thresholds. An absolute threshold is a fixed value that applies to the entire point cloud. On the other hand, a relative threshold is applied by comparing the ratio of the temperature of a point to the temperatures of the neighbouring points. This helps to overcome the problem of non-uniform distribution of temperature across the point cloud. Then, points which have temperatures greater than a predetermined upper threshold will be considered as occupying peak regions whereas points which have temperatures less than a predetermined lower threshold will be considered as occupying valley regions. This is illustrated in Figure 3, where thermal intensity peak and valley regions are highlighted with respect to the original point cloud.



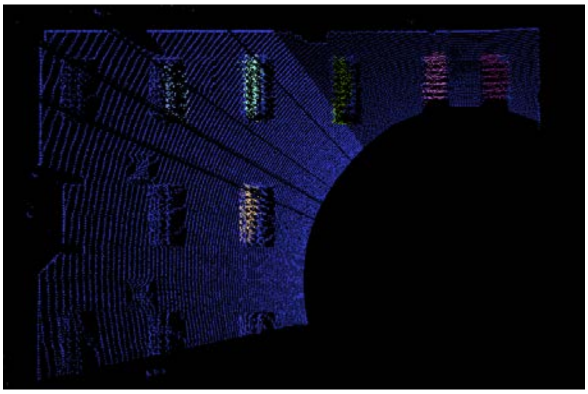
(a)



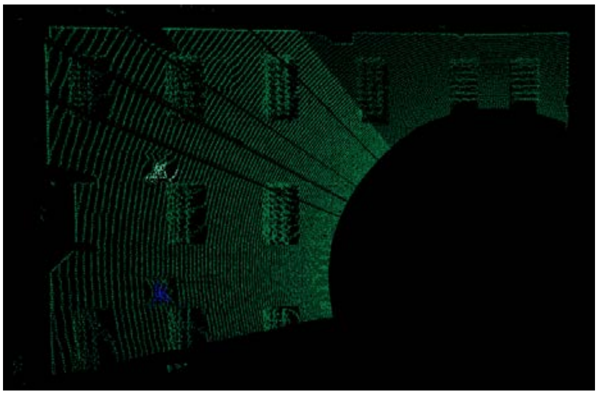
(b)

Figure 3: Thermal intensity (a) peak and (b) valley regions highlighted in red.

Finally, the peak and valley regions are subdivided into individual elements using a clustering algorithm. The clustering algorithm works by randomly sampling seed points and expanding individual clusters by incrementally assigning points which are geometrically close to each other to be part of the same cluster. This procedure is repeated until all points are assigned to a unique cluster. However, clusters with less than 50 points are filtered out since it is assumed that clusters which are too small do not originate from building elements but are a result of noise in the data. A visualization of this step is shown in Figure 4, where individual point cloud clusters are highlighted in different colours. Each point cloud cluster is considered a prediction of a building element and the centroid of the point cloud cluster is taken to be the centroid of the predicted building element.



(a)



(b)

Figure 4: Point cloud clusters of detected building elements: (a) lighting elements and (b) cooling elements

4 Results

The proposed method is evaluated with laser-scanned point clouds of an indoor laboratory in Georgia Institute of Technology. Two different laser scans were collected from the site. The thermal mapping process described in Section 3.2 was used to map the temperature information from thermal images to the point cloud. Figure 5 shows the resulting thermal-mapped point cloud in an indoor lab setting.

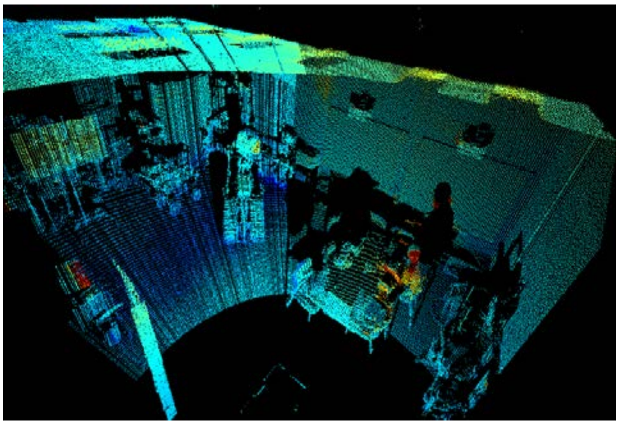


Figure 5: Thermal-mapped point cloud in an indoor lab setting

Next, the method proposed in Section 3.3 was used to detect and localize lighting elements and cooling elements. The accuracy of the proposed building element recognition method is evaluated with three different metrics. The precision metric measures the number of correct predictions of building elements compared to the total number of predictions made. The recall metric measure the number of correct predictions of building elements compared to the actual number of building elements present in the original scene. The root mean squared error (RMSE) metric measures the distance error between the centroid of a predicted building element and the ground truth centroid which is obtained manually. Table 1 shows the precision, recall, and RMSE results for lighting and cooling elements in two different laser scans (labelled A and B respectively).

Table 1: Precision, recall and RMSE for each building element

Building element	Precision	Recall	RMSE (m)
Lighting A	1.00	0.86	0.146
Cooling A	1.00	1.00	0.098
Lighting B	1.00	0.75	0.277
Cooling B	1.00	1.00	0.489

5 Discussion

The performance of the proposed recognition system can be analysed with respect to the precision, recall, and RMSE metrics. Table 1 shows that the proposed method is able to achieve perfect precision in terms of the building elements that are recognized. This is because the combination of thermal information and geometric information helps to eliminate false positives and the resulting detections can be labelled as building elements with high confidence. However, in the case of recall rates, the method only achieves around 80% for lighting elements. This is due to the fact that the laser scan data collected is non-uniform in resolution. For regions in the point cloud that are far away from the laser scan origin, the point cloud resolution is low and the thermal mapping process is error-prone. Thus, building elements that are located far away from the laser scan origin tend to result in missed detections. Finally, the results for RMSE showed that the proposed method can localize building elements to within about 0.25m of the ground truth. The high RMSE value for the “Cooling B” test set is due to an outlier where the low temperature region is mistakenly assigned to an adjacent patch so the predicted centroid is inconsistent with the ground truth centroid.

6 Conclusion

This research proposes a method for recognizing building elements from thermal-mapped point clouds based on regions of high and low thermal intensity. The proposed processing pipeline involves data collection from a mobile robot using both laser scanners and a thermal camera where temperature mapping can be performed from thermal images to point cloud. Next, the ceiling region containing the building elements of interest is identified and extracted from the point cloud. Segmentation of peak and valley thermal intensity regions is carried out based on absolute and relative temperature threshold values. The identified point cloud clusters can be each associated with a building element and localized based on the cluster center. The proposed building element recognition method was validated with two sets of laser scan data collected in an indoor laboratory using the metrics of precision, recall and RMSE. Experimental results showed that the method achieved perfect precision, which means that there are no false positive results. In addition, a promising 90% recall rate and 0.25m RMSE was achieved as well. Future work in this area would involve increasing the types of building elements that can be recognized as well as quantifying the accuracy on a larger dataset.

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