Building heat loss evaluation using artificial intelligence methods and thermal photogrammetry*

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Abstract
Thermal point-clouds are becoming increasingly relevant in times of climate change, and it is essential that efficient methods for calculating heat losses exist. Whilst heat losses can be calculated by means of simulations and / or on-site expertise, such methods can consume significant financial resources. With the rise of artificial intelligence methods and the availability of thermal imaging technologies, they can be utilized for the automation of such calculations. We propose a methodology for calculating heat losses based on thermal photogrammetry and imaging. By segmenting thermal point-clouds for buildings and removing noise from the result of the segmentation, the output is a point-cloud that is void of unnecessary data for heat loss calculations. This model is then converted to a mesh, and heat losses are calculated for each triangle of the mesh by mapping the area of each triangle to the surface temperature of it based on the closest RGB color from the thermal images, resulting in a direct map between triangle surface area and triangle surface temperature. Our results indicate that such a methodology can be used for more efficient heat loss calculations, as we have achieved a mean average error of 0.42 kW or 0.14 kW depending on whether the ground is considered during calculations or not, respectively. Further work could explore calculating heat losses for multiple buildings at a time, calculating heat losses during different seasons. Furthermore, different emissivity and thermal loss coefficients can be used, as using static values for these parameters limits the accuracy of the calculations.

Keywords
Thermal photogrammetry, point-clouds, building heat loss evaluation, artificial intelligence, point-cloud segmentation, building segmentation.

1. Introduction

Buildings account for more than 36 % of all CO_2 emissions in the EU. For this reason, it is important to be able to evaluate the thermal losses of buildings accurately and efficiently. More thermally efficient buildings are not only more comfortable for their users, but also contribute less to greenhouse gas emissions. The detection and evaluation of thermal losses using traditional means can be expensive both in terms of time and finances. With the rise in popularity of various artificial intelligence algorithms, such tasks can be delegated at least in part to machine learning methods that can solve them efficiently.

Thermal anomalies, like cold bridges, can be detected by the use of thermal imaging [1,2]. Ristič [1] used thermal images to evaluate the thermal efficiency of a museum in Belgrade. The author concluded that the building had a low thermal efficiency and had detected several cold bridges via thermal imaging. According to the author, such phenomena can be identified even with a low-resolution thermal camera, as these points of interest are picked up due to the high sensitivity of such cameras. Zumr [2] also used thermal images for identifying thermal phenomena and other

**IVUS2024: Information Society and University Studies 2024, May 17, Kaunas, Lithuania*
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characteristics of dams in the Czech Republic. The author has identified thermal properties of the dams that would not have been possible without the use of thermal imaging hardware.

For digitizing buildings, point-cloud models are often used [3-10]. When it comes to analyzing and processing point-clouds, Paiva [5] had pointed out several points about the challenges for these tasks:

- Analysis of large point clouds require more resources,
- Noise can be introduced during the point-cloud creation process,
- Certain spots can be missed during the point-cloud creation process, introducing holes in the output point-cloud model.

Regarding incomplete point-cloud models, this challenge is especially noteworthy in the context of creating digital twins of buildings and cities [3]. Despite these challenges, several authors have utilized thermal models for the purpose of evaluating the thermal state of different objects. Gil-Docampo [11] used thermal photogrammetry as means of convenient building inspection, as a tool for analyzing thermal anomalies. Zhu [12] created a thermal point-cloud based on a colorless point-cloud and thermal images by mapping the pixels from the thermal images to the points in the point-cloud. Ponti [13] used thermal point-clouds for monitoring the thermal properties and degradation of a rock wall in different times of the year. Dlesk [14] augmented a RGB point-cloud with a additional dimension of data – temperature from thermal images, resulting in a point-cloud with thermal information for each point of data. Similar work was performed by Hou [15], in which they provided a framework for creating a mapping between thermal images, RGB images and colorless point-clouds. Macher [16] utilized thermal point clouds for detecting windows in building facades due to the visible thermal properties of windows when viewed through thermal images. In a similar way, Jarząbek-Rychard [17] constructed a thermal point-cloud from RGB and thermal images for the use of automatically detecting windows and other façade openings, like doors. Among other work, Biswanath [18] proposed an idea of mapping a thermal point-cloud to a 3D model of a building with the goal of enriching a building model with additional textures that represent actual surface temperature data.

In regards to calculating thermal heat losses for buildings by utilizing thermal photogrammetry, there were no identified works in which such an approach was studied, although thermal bridges and certain façade elements have been identified based on their heat print in thermal photogrammetry models.

2. Methodology

In our work, we propose a methodology for calculating thermal losses for buildings by using artificial intelligence methods and thermal photogrammetry. Our proposed methodology for evaluating thermal losses relies on both thermal images and point-clouds that are created by using thermal images.

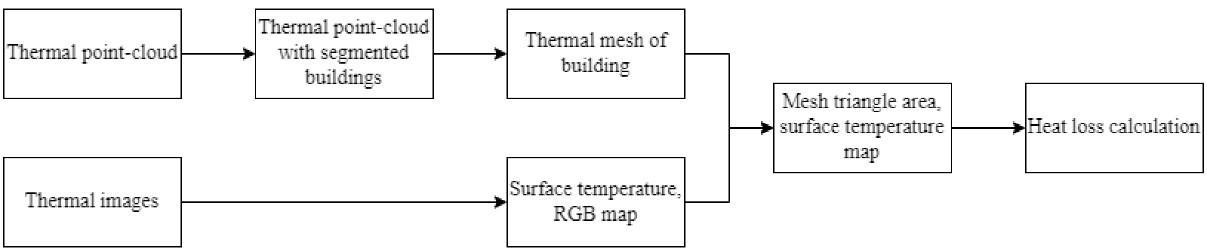

Figure 1. Methodology for work, detailing the process of calculating heat loss

As can be seen in Figure 1, thermal loss evaluation was performed by acquiring specific data from thermal images and thermal point-clouds – areas of different surfaces of the building and surface temperatures for each of the surfaces. To acquire the required surfaces, outlier points must be removed from the point-cloud, such that all points left in the point-cloud should be of the building. To acquire the temperature for each of the surfaces, the RGB color of each point in the point-cloud must be mapped to a surface temperature value. The results were evaluated against a white-box model, in which the thermal losses were calculated based on the dimensions and thermal characteristics of the materials present in the building envelope. Since such a dataset does not exist (that would include true heat loss values to evaluate against), it was decided to create a custom dataset for this task.

The thermal images were captured using a DJI Mavic 2 Enterprise drone and include thermal data encoded for each pixel of the images.

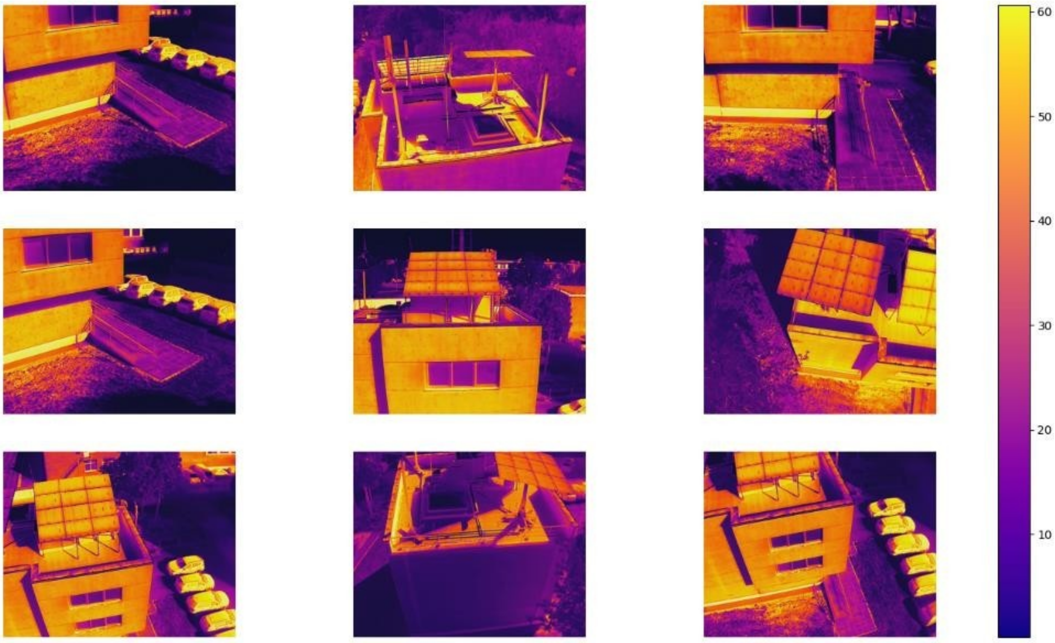

Figure 2. A sample of the thermal images used in dataset.

As it can be seen from the Figure 2, the temperature in the sample images varies from about 0 to 60 °C and certain surfaces of the building are visibly heated. Due to the challenge of creating geometrically accurate photogrammetry models, it was chosen to work using images that were taken in August. For decoding the temperature data, the DJI Thermal SDK was chosen due to its' compatibility with the images taken with the drone. For decoding the temperature data using the SDK, an emissivity parameter ε must be supplied. Since the materials on the surfaces of the building in question are varied, it was chosen to use the default ε value of 0.95. In total, the dataset consists of 362 thermal images, in which, as can be seen from x, the temperature values are between -10.8 and 200 °C (see Table 1).

Table 1
Metrics for the thermal images in the dataset

Metric	Value, ° C
Minimum	-10.80
Maximum	200.39
Mean	28.06
Standard deviation	9.60
Variance	92.22

Since there are no publicly available point-clouds for this specific task, we have generated a thermal point-cloud from the previously mentioned images. The point-cloud was generated from a photogrammetry model that was created using Bentley Systems Context Capture (see Figure 3).

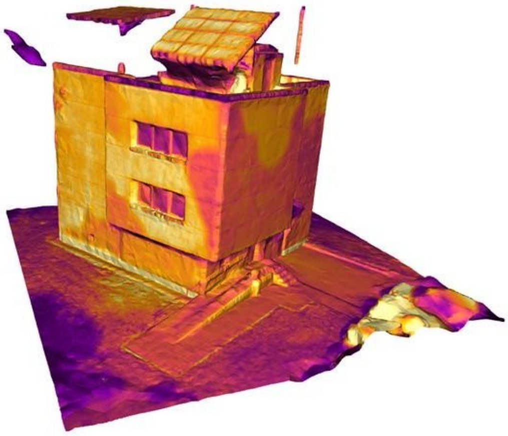

Figure 3. Thermal point-cloud used in dataset

The software takes input images and uses photogrammetry algorithms to form a 3D representation of the scene in question. As can be seen from the figure, there is a significant amount of noise surrounding the building. Much of this noise is the ground-level, which must be cleared up before pursuing building energy calculations. Additionally, there are automobiles that should not be considered during the calculations. Regarding preparing the point-cloud for further use in building energy calculations, several approaches were chosen and compared. The first approach was to use a plane segmentation algorithm for detecting and removing irrelevant planes from the point-cloud, whilst preserving planes that correspond to the building surfaces. This approach was realized via RANSAC segmentation. RANSAC is an algorithm that was originally used for finding an optimal line for a 2D dataset, but it can be adapted for finding an optimal plane in 3D space, as well. The unsupervised machine learning algorithm works by detecting clusters of points by finding the minimal sets that correspond to certain geometric primitives, like planes, roofs, etc. [5]. Another approach for segmenting the building in the point-cloud was considered – via point-cloud segmentation algorithms. There are several popular point-cloud segmentation algorithms that are capable of robust building and other object segmentation in large point-clouds. Several of the most popular algorithms are KPConv and RandLA- Net. Both algorithms are deep learning models that were trained using various point-cloud datasets. In our experiments, pre-trained models trained on the Paris-Lille3D dataset were used, as models trained on this dataset seem to perform best in segmenting thermal point-clouds.

The results of building segmentation using RANSAC, KPConv and RandLA-Net algorithms were compared using a unified benchmark. The results of the algorithms were compared to the bounding-boxes that represent the real surfaces of the building and were evaluated using different error metrics. Amongst the error metrics used, was

$$Precision = \frac{TP}{TP + FP}, \quad (1)$$

$$Recall = \frac{TP}{TP + FN}, \quad (2)$$

$$F1 = \frac{2 \times TP}{2 \times TP + FP + FN}, \quad (3)$$

$$IoU = \frac{TP}{TP + FP + FN}, \quad (4)$$

$$d_C = \sum_{x \in S_1} \min_{y \in S_2} \|x - y\|_2^2 + \sum_{x \in S_2} \min_{y \in S_1} \|x - y\|_2^2, \quad (5)$$

where TP – true positives, FP – false positives, FN – false negatives and S – point-cloud, used exclusively for comparing via Chamfer distance (see Equation 5).

The benchmark was performed using a Ryzen 3700U CPU and 16 GB of DDR4 memory. KPConv and RandLA-Net performed better than RANSAC, whilst KPConv performed best out of the three algorithms (see Table 2).

Table 2
Results of different building segmentation algorithms

Metric	RANSAC(n=3, n_{iter}=1000, $thres$=0.3, n_p=7)	RandLA-Net(bs=4, lr=0.01, lr_{decay}=0.95)	KPConv(bs=1, lr=0.01, lr_{decay}=0.98477)
Precision	0.60	0.67	0.68
Recall	0.91	0.94	0.95
F1	0.73	0.79	0.80
IoU	0.57	0.65	0.66
Chamfer distance	-1.28	-0.76	-0.70

Although the building in the point-cloud was segmented, its segmentation result included a significant amount of noise, most notably – cars and other objects that have the potential to significantly skew the results of further calculations. To address this, it was chosen to statistically remove noise using K-nearest neighbors. Statistical outlier removal ensures that only points that have a certain amount of neighbors n within an average distance threshold of s remain as inliers. Statistical outlier removal was applied to the results of KPConv, which resulted in a significant number of outliers being detected (see Figure 4).

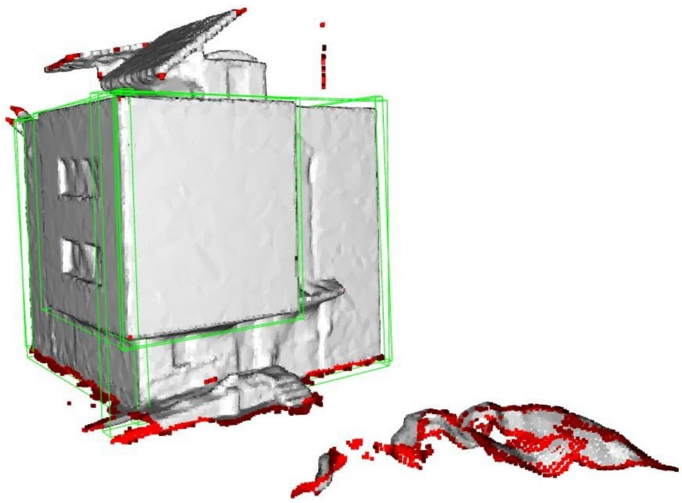

Figure 4. Segmented point cloud using KPConv, with statistical outlier removal applied afterwards

Regarding the numerical results of the outlier removal, the most significant increase in accuracy is according to the Chamfer distance (increase of 0.02), whilst there is also a small accuracy decrease according to the Recall metric (decrease of 0.01).

For retrieving the surface areas of the different surfaces of the building, the point-cloud was converted into a mesh using Poisson surface reconstruction. Poisson surface reconstruction is a robust algorithm for converting point-clouds to meshes by means of converting the task to a well-posed sparse Poisson problem, resulting in a noise-resilient algorithm [19]. Such a conversion enables analyzing the object as a collection of inter-connected triangles, each with their respective area and color. The average RGB color of the three triangle vertices is mapped by Euclidean distance to the closest temperature value from the thermal images. This results in a mapping between each triangle in the mesh and its respective surface temperature, as can be seen in Table 3.

Table 3
Sample of mesh triangles with mapped area and temperature values

Mesh triangle area, m^2	Mesh triangle surface temperature, °C
0.0008	25.5305
0.0026	23.2761
0.0009	29.3719
0.0023	23.0339
0.0008	25.5305

The data can be used to calculate heat loss through the building envelope via Equation 6.

$$Q = U \times A \times (T_i - T_p); \tag{6}$$

where U is the heat transfer coefficient, A is the surface area, T_i and T_p are the indoor and outdoor temperatures.

Since we are not familiar with the indoor temperature of the building in question during the time that the thermal images were taken, different temperature values between 20 and 25 were considered. A U value of 0.202 was used, as it is a common value for walls, which is the dominant type of surface in the building. Lastly, the results of the calculations were compared to a white-box model of the building in question, in which the calculation of Q was based on known measurements of the building and its' structural materials that make up the envelope.

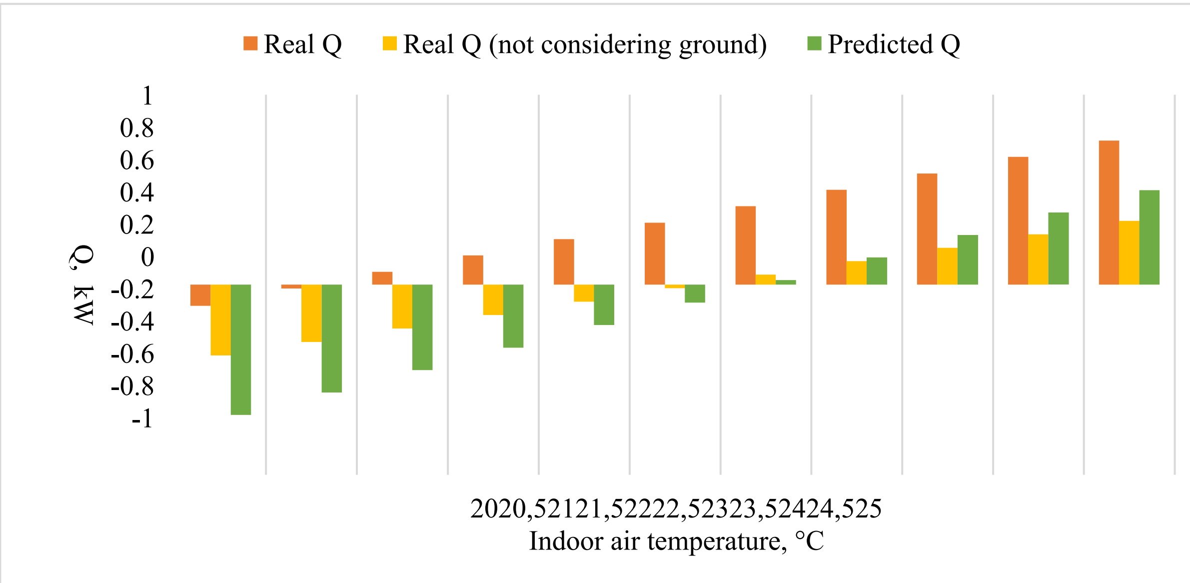

Figure 5. Results of heat loss calculation by using thermal point-clouds and images

As can be seen from Figure 5, the predicted Q values are close to the real Q values, especially when the ground layer (which is not visible to the drone at the time of capturing the thermal images) is not considered during calculation. The mean average error for the calculations is 0.42 kW when the ground layer is considered, and 0.14 kW when it is not.

3. Conclusion and further work

The most common use case for thermal point-clouds when it comes to analyzing the state of buildings – identifying cold bridges and other thermal efficiency phenomena visually. When it comes to evaluating the thermal energy loss of a building, the thermal information of the surfaces of the building envelope that is captured in the model can be used to automate this process. Since a photogrammetry-based point-cloud contains a geometrically accurate representation of the building, this can be used together with thermal information to evaluate thermal losses of the building without the need for constructing white-box models.

Since there is no publicly available dataset that could be used for such a task, we have created our own dataset utilizing 362 thermal images and a point-cloud that was created based on a thermal photogrammetry model constructed from said images. Whilst creating the dataset, we faced difficulties in creating thermal photogrammetry for the heating season, which is why thermal images and models from August were utilized. Using our approach, the point-cloud of the building is prepared by segmenting it using a pre-trained KPConv model – a deep-learning based algorithm for point-cloud segmentation and is further cleaned up by statistical outlier removal. The segmented model is then converted into a mesh via the Poisson surface reconstruction algorithm and the surface areas and colors of each of the triangles of the mesh is calculated. The color of each triangle is mapped to a surface temperature via the closest color based on the Euler distance, which results in a mapping of surface temperature value and triangle area for each of the triangles in the mesh. Lastly, this mapping is used in the calculation of thermal losses based on Equation 6.

Our approach yielded results that have a mean average error of 0.42 kW or 0.14 kW depending on if the ground is considered, or not, respectively. The results resemble the true Q values that are based on white-box simulations of the building in question. Although the results cannot be directly compared to other studies due to the custom nature of the dataset, the methodology should apply to other works if the thermal point-cloud geometry and thermal of the images accuracy are high.

For further work, it would be suggested that heat losses would be calculated for different seasons, as in our work, they were calculated only during the summer season, in which thermal losses are minimal or sometimes even negative. It is also suggested that an additional step of segmenting the different elements of the building envelope and façade should be segmented, e.g. the roof, windows, etc. and that based on this information, different ε values would be set dynamically when calculating the surface temperature from the thermal images.

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