Heat Loss Estimation using UAS Thermal Imagery

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***Abstract*— Heat Loss Quantification (HLQ) is a key step in improving the thermal performance of buildings. Affordable infrared (IR) cameras mounted on an unmanned aerial vehicle (UAV) make low cost heat loss quantification using IR imaging feasible. This technique also facilitates capturing the heat loss information in hard-to-reach areas using UAVs. In this paper, a series of pre-processing steps such as dominant color isolation (DCI), background elimination and key point identification as part of the heat loss quantification are discussed. The thermal transmittance (or the U-value) of various buildings at the University of North Dakota, in Grand Forks, ND, are estimated from the images captured by aerial thermal cameras mounted on UAVs.**

Keywords: Infrared (IR) thermography, Overall heat transfer coefficient (U-value), Unmanned aerial vehicles (UAVs)

I. Introduction

An unmanned aerial system (UAS) consists of various unmanned aerial vehicles (UAVs), one or more control units, communication systems, and may contain launch and recovery platforms. Affordable UAVs and their increased performance with low energy consumption made them great candidates for alternative means of data collection. UAVs provide several advantages over traditional means of data collection, particularly for aerial thermography. Due to their advantages, the use of UAVs are becoming more widespread, and thus more reliable techniques for data collection and analysis are becoming increasingly valuable.

While analyzing an image, the segments of the image that interfere with certain analysis procedures must be disregarded. One simple example is when it is desirable to average the temperature of an entire face of a building. In nearly all cases, an image will not contain an entire face without including some undesired elements. Most often this set includes elements such as the sky, the ground around the building face, or trees. In more difficult cases, the image may also include other buildings. These elements will alter the results of averaging image pixels, and must be excluded from this process.

A. Motivation and Contribution

Quantification of heat loss in buildings is an available tool for those who wish to optimize energy efficiency in existing structures. In its current state however, the process is costly and meticulous, and often involves 3D modeling and other reconstructive tools. This limits the availability of the tool primarily to well-funded projects [1]. Thermal imaging of buildings using unmanned aerial systems (UAS) has become increasingly inexpensive, and yields the potential to make heat loss quantification an affordable option should the analysis of collected thermal images become feasible.

In this work, heat loss of the buildings is estimated using thermal images captured using Zenmuse XT Radiometric FLIR 640x512 (30Hz) thermal drone camera. In order to get meaningful information from the captured IR images, the images are pre-processed, which involves separating the building from the background objects and detecting edges that constitute the building. Two techniques, namely dominant color masking and key-point identification, are used to extract meaningful data.

The remaining sections of the paper are divided as follows: section II: Literature Review, section III: Methodology, section IV: Conclusion and Future Work, and section V: Acknowledgement.

II. Literature Review

Several methods are discussed in literature to evaluate the overall thermal performance of the buildings. In qualitative measurements, various parts of the buildings are identified only when thermal bridging is observed [2]–[7]. A thermal bridge is a sub-part, an area or a component of an element that provides more heat flow than the surrounding elements. The quantification of thermal loss is not required in these measurements, whereas the objective is to detect any anomaly present from the evaluation of the thermal pattern.

Identifying various parts for thermal anomalies may help to foresee various retrofit interventions which in turn reduces maintenance cost of the buildings.

On the other hand, thermal anomalies are quantified in quantitative heat loss assessments [8]–[10]. In other words, it gives a value that represents the number of thermal anomalies present in the investigated object. One way of performing the quantitative assessment of a building is by providing the overall thermal transmittance of different parts of the buildings, generally known as the “U-value”. The U-value can also be defined as the rate of heat that flows, in steady state conditions, through one square meter of the wall (or the inspected part of the wall) from/to the outside air when the temperature difference between the inside and outside is one Kelvin. The unit of U-value is $Wm^{-2}K^{-1}$. Various techniques of evaluating the overall heat transmittance of the buildings have been reported in literature [11]–[16]. These techniques can be categorized into two parts: (1) active measurement, and (2) passive measurement. In active measurement, actual measurements are taken from the building elements, including surface temperature of the wall, inside and outside air temperatures, wind velocity, and many more. In passive measurement, no direct measurements are taken from the building elements. Instead, they may be taken from the coeval buildings and then a theoretical approach is applied to evaluate the overall heat transmittance of the building.

In [17], the authors estimated the heat loss in buildings using UAVs, but the U-value, which is a prominent feature to estimate the thermal performance, is not addressed. The authors used segmentation and classification in IR images to identify the associated large heat-loss areas, but fail to provide a quantification index that can capture the heat loss. In the following survey, we address the various methods used to quantify the heat-loss.

In 2008, Madding [18] proposed the following formula to estimate the U-value:

$$U = \frac{4\varepsilon\sigma T_m^3(T_w - T_{ref}) + h(T_w - T_{in})}{T_{in} - T_{out}} \tag{1}$$

where ε is the wall emissivity, σ is the Stefan-Boltzmann constant, $T_m = \frac{T_w + T_{ref}}{2}$, h is the thermal convective coefficient, T_w is the inside wall temperature, T_{ref} is the reflected temperature, T_{in} is the indoor air temperature, and T_{out} is the outdoor air temperature. The numerator has both radiative and convective terms, whereas the difference in air temperature from the inside to the outside of the building wall is expressed in the denominator.

In 2011, Fokaides and Kalogirou [19] proposed a formula similar to Madding's formula, in which the wall temperature is used in place of the mean temperature in the radiative term. The U-value is given as

$$U = \frac{4\varepsilon\sigma T_w^3(T_w - T_{ref}) + h_{in}(T_w - T_{in})}{(T_{in} - T_{out})}, \tag{2}$$

Nomenclature

Symbols

ε	Thermal emissivity
ε_ν	Wall spectral emissivity
h	Thermal convection coefficient $[W/m^2K]$
σ	Stefan-Bolzmann constant $[W/m^2K^4]$
T	Temperature $[K]$
U	Overall heat transfer coefficient $[W/m^2K]$
v	Wind speed $[m/s]$

Indices

in	Indoor
m	Mean
ref	Reflected
out	Outdoor
w	Wall

where ε is the wall emissivity, σ is the Stefan-Boltzmann constant, h_{in} is the indoor thermal convective coefficient, T_w is the inside wall temperature, T_{ref} is the reflected temperature, T_{in} is the indoor air temperature, and T_{out} is the outdoor air temperature.

Dall'O' et al. [20] proposed a different formula in which the radiative term is not considered. The overall U-value is given as

$$U = \frac{h_{out}(T_w - T_{out})}{T_{in} - T_{out}}, \tag{3}$$

with $h_{out} = 5.8 + 3.8054v$ where v is the wind speed, T_w is the inside wall temperature, T_{in} is the indoor air temperature, and T_{out} is the outdoor air temperature.

Then in 2015, Albatici et al. [21] proposed the following formula:

$$U = \frac{\varepsilon_\nu\sigma(T_w^4 - T_{out}^4) + 3.8054v(T_w - T_{out})}{T_{in} - T_{out}}, \tag{4}$$

where ε_ν is the wall spectral emissivity, σ is the Stefan-Boltzmann constant, T_w is the inside wall temperature, T_{in} is the indoor air temperature, and T_{out} is the outdoor air temperature.

III. Methodology

This section discusses the detailed methodology used in this work. The images used are taken of various buildings on the University of North Dakota (UND) campus by SkySkopes, a professional UAS flight operator headquartered in Grand Forks, ND, USA. The images were taken by a drone using the Zenmuse XT Radiometric FLIR 640x512 (30Hz) thermal drone camera. These are gray scale images which are first processed using Sense Batch [22], a thermal image processing software created by Sky Eye Innovations, that can be used to extract the temperature data in the form of a CSV file. These CSV files contain the temperature reading at each pixel in the image as measured from the FLIR camera. These gray scale images and corresponding CSV files are analyzed using Wolfram Mathematica 11.3 software [23]. Upon data collection, the images are pre processed to remove the background and focus on the region of interest. After preprocessing, the temperature readings of the corresponding buildings can be collected and the average U-value for each building can finally be computed.

A. Data Collection

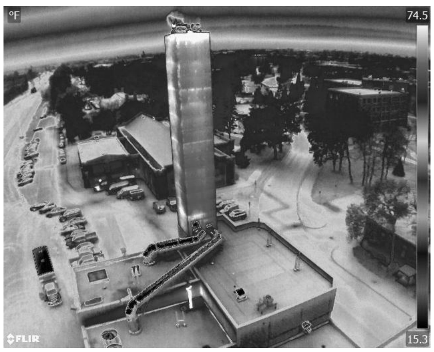
Using a drone equipped with a FLIR camera, SkySkopes took hundreds of infrared images of various buildings on the UND campus. Fig. 1 shows thermal imagery of selected buildings on the campus. Prior to data collection, a piece of aluminum foil and black tape were placed on each building, as seen in Fig. 2. These were used to calculate the reflected temperature and emissivity, respectively. A HOBO sensor was placed inside each building being photographed to measure the temperature inside the building.

Temperature data from the images is extracted using FLIR software. This data is then used to calculate the temperature of the aluminum foil, the temperature of the black tape, and

(a) Robertson-Sayre Hall, UND

(b) Columbia Hall, UND

(c) Education Building, UND



(d) Steam Plant, UND

(e) Twamley Hall, UND

(f) Robertson-Sayre Hall, UND

Fig. 1. Thermal images of various buildings in the University of North Dakota campus taken by SkySkopes.

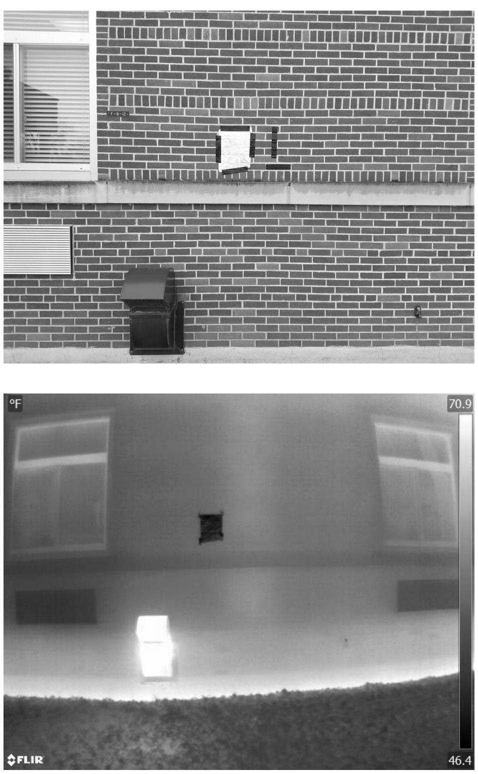


Fig. 2. Aluminum foil and black tape placed on the Columbia Hall building at the University of North Dakota prior to capturing thermal images.

the wall temperature. The temperature of the aluminum foil is used to calculate the reflective temperature, which must be eliminated in order to find the actual temperature of the building [24]. The temperature of the black tape is used to calculate the emissivity. The outdoor temperature is obtained from the HOBO sensor that accompanied the drone and the wind speed measurements are obtained from weather data.

B. *Pre-processing: Background Elimination*

In order to quantify the heat loss of a building accurately, it is essential to first identify the correct portions of the image that represent a building. Generally, when a building image is captured using an IR-camera mounted on a UAS, the image may contain additional unwanted objects like trees, ground, roads, sky etc. These elements, if not carefully eliminated from the image, may lead to error in the overall heat loss quantification. An example of an unwanted object present in an IR image is shown in Fig 2.

In order to eliminate the unwanted background object, we use an assisted masking algorithm along with Dominant Color Isolation (DCI). The assisted masking algorithm uses point placement to draw a polygon around a region of interest, and eliminate unwanted background around a region of interest. This process is illustrated in Fig. 3.

DCI separates an image into various dominant color channels while masking the remaining channels. In this method, the distance between different colors is calculated and the colors whose distances are within a threshold are clustered.

(a) (b) (c)

Fig. 3. An example of background elimination.

In order to calculate the distance, LAB color space is used where L denotes luminosity and A and B denote two different colors. The range of A and B is within -1 to +1 where -1 represents green and blue, and +1 represents magenta and yellow for A and B, respectively. Consider an example, a color may be represented using a 3-D vector like {0.7, 0.9, -0.4}, where 0.7 denotes luminosity, 0.9 and -0.4 denote the corresponding values for color A and B, respectively. An image within a cluster is masked such that all colors with distance less that the threshold are white, and all colors with distance greater than the threshold are black, as shown in Fig.4. Note that certain masks can be combined to eliminate background objects and to correctly form the edges that separate a building from its surroundings.

Multiple image processing algorithms are in the development phase to identify keypoints in each image, which can be used to identify images of the same building taken from different angles. These points can then be used to identify the mathematical relationships that describe how the building is stretched, skewed, rotated, etc. in each image. The images can then be rotated and skewed according to this calculation, allowing them to be overlaid and temperature data for each particular area on the building to be averaged automatically. The ability to average temperature data across multiple images will reduce error in temperature calculations.

The images in Fig. 5 show two thermal images of Twamley Hall taken from different angles. Image keypoints are found using the SURF keypoint detection method. Each keypoint found is numbered on the first image, and the corresponding keypoint is also denoted with the same number on the second image. The keypoints are then put into groups based on the distance to neighboring keypoints. Clustered keypoints can be used to automate the image analysis process and automatically detect images of the same building.

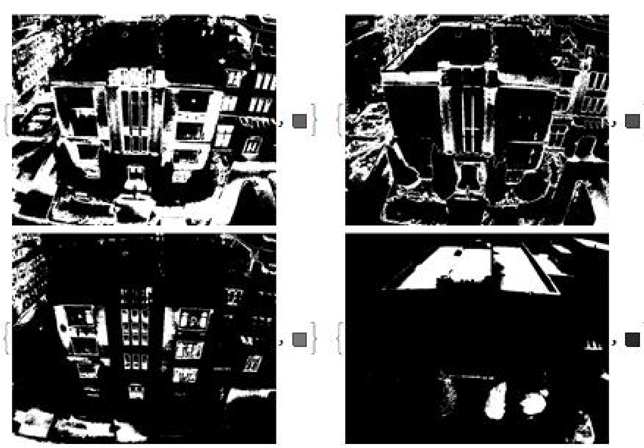
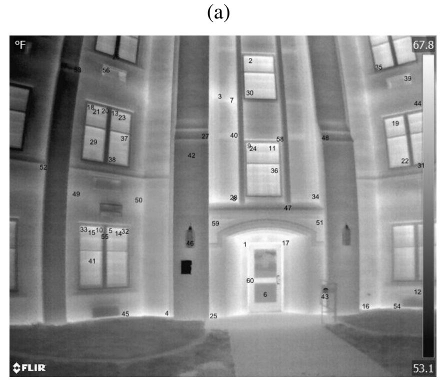


Fig. 4. Dominant Color Isolation (DCI).

C. Heat-loss Quantification

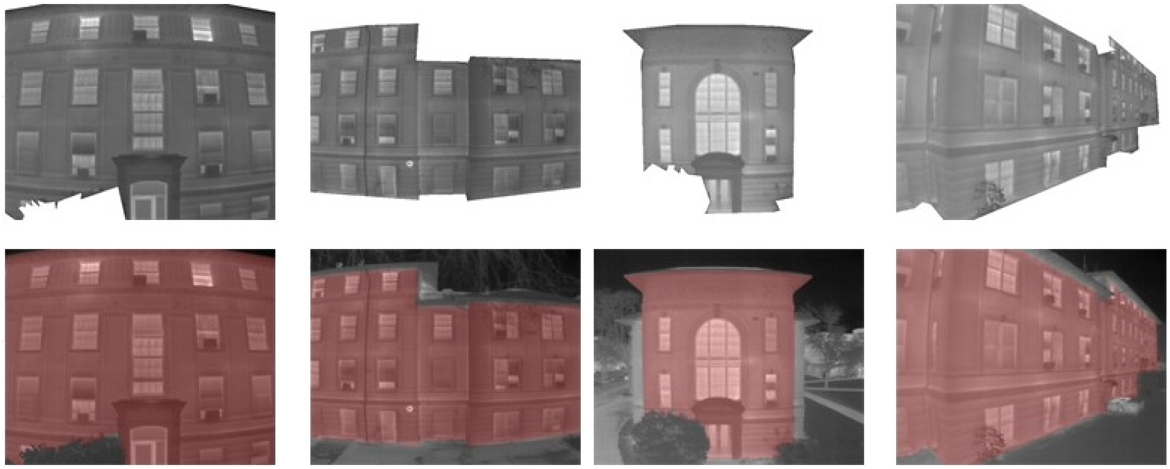
In order to quantify the heat loss, equation 4 is used, with thermal images to measure wall temperature, a HOBO sensor to obtain inside and outside air temperature, and historical weather data to estimate the wind velocity. Assuming wall spectrum emissivity to be 1, and replacing the Stephen-Boltzman constant σ by $5.67 \times 10^{-8}\, Wm^{-2}K^{-1}$, we can obtain values for all the variables and calculate a U-value.

(a)



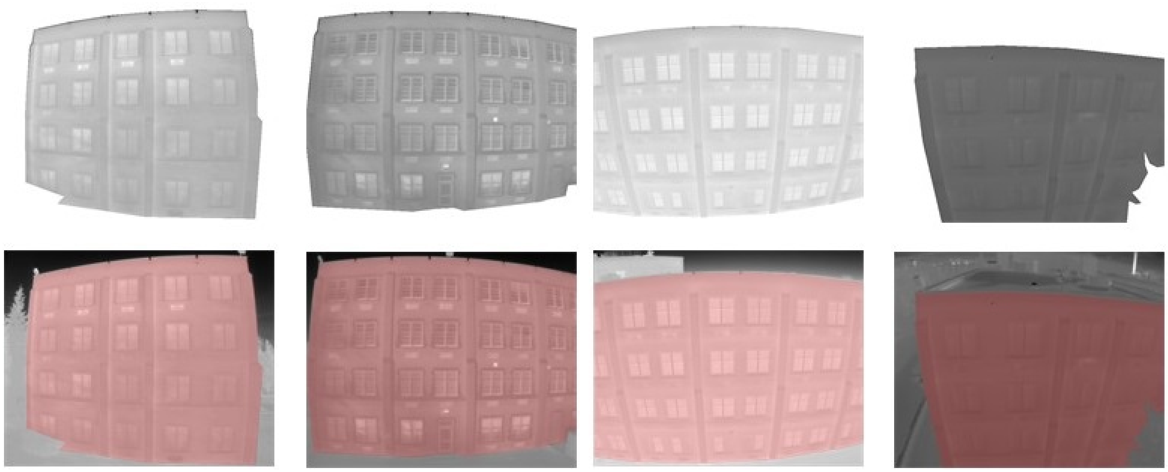
(b)

Fig. 5. An example of image keypoint clustering.



(a) Face 1 (b) Face 2 (c) Face 3 (d) Face 4

Fig. 6. U-value quantification for Robertson-Sayre Hall.



(a) Face 1 (b) Face 2 (c) Face 3 (d) Face 4

Fig. 7. U-value quantification for Twamley Hall.

Building Name	Face 1	Face 2	Face 3	Face 4	Average
R-S Hall	0.581	4.27	-0.779	-1.837	0.55875
Twamley Hall	2.867	6.577	0.495	-2.61421	1.8311975

Table 1. Average U-value for Robertson-Sayre (R-S) Hall and Twamley Hall.

When calculating the U-value for a desired thermal image, the radiometric data must first be extracted, and saved as a CSV file. The image and associated CSV file are then imported into Mathematica to undergo pre-processing, where only the desired data is used in the calculation phase. During the calculation phase, data from the HOBO sensor is used for the indoor and outdoor temperatures, historical weather data is used to estimate wind speed, emissivity is assumed to be 1, and the wall temperature is the radiometric value obtained for a given image pixel. This allows for a matrix of U-values to be calculated (after pre-processing, as shown in Fig. 3) for the desired image corresponding to each image pixel. From the U-value matrix, desired information can be extracted, such as average U-value for a building face, as shown in Fig. 6 and Fig. 7. This particular result can be seen in Table 1.

IV. Conclusion and Future Work

In this paper, the U-value of various campus buildings at the University of North Dakota in Grand Forks, ND is calculated using thermal images captured by an unmanned aerial system (UAS). The pre-processing phase focused primarily on assisted masking and Dominant Color Isolation (DCI) to remove unwanted background objects. The future work includes automating the pre-processing phase further. The DCI algorithm has strong potential to be applied with machine learning algorithms to produce fully automated accurate masks of thermal images, and will also be of interest in future works.

V. Acknowledgement

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