Edge Detection and Dominant Color Masking of Thermal Imagery Data Sets

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***Abstract*–Heat loss Quantification (HLQ) is a key step in improving the thermal performance of buildings, which is important for energy audit applications. The purpose of this research work is to process thermal imagery data sets obtained from unmanned aerial systems (UAS) to quantify the thermal transmittance (U-value). In order to gain meaningful data, the images must undergo a series of pre-processing steps that include: edge detection, and a background elimination process to extract a region of interest from the image for more accurate analysis. Specifically, we propose a Dominant Color Isolation (DCI) algorithm for pre-processing of imagery enabling image analysis to be performed without cluttered effects from the sky, ground, trees, or other objects.**

Keywords: Image analysis, Image edge detection, Object detection

I. INTRODUCTION

Quantification of heat loss in buildings is an available tool for those that 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 a feasible. In this work, we investigate a background subtraction method to be applied to thermal imagery for the purposes of quantifying the heat loss using these images. With proper analysis of thermal imagery, there are numerous methods proposed in order to quantify the heat loss through a building envelope, by finding the overall heat transfer coefficient, or the U-value. Currently, there are no universally accepted theoretical approaches to calculate the U-value. Consequently, several formulas have been proposed in literature aimed to accurately calculate this U-value [2-5]. The images used in this work are taken of various buildings on the University of North Dakota (UND) campus by SkySkopes, a professional UAS flight operator headquartered in Grand Forks, North Dakota, USA. The images were taken from a drone using the Zenmuse XT Radiometric FLIR 640x512 (30Hz) Thermal Drone Camera. These are grayscale images which are first processed using Sense Batch [6], 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. From here, the grayscale images and corresponding CSV files are analyzed using Wolfram Mathematica 11.3 software [7].

In the analysis, the images need to be processed in order to eliminate the background. We are only interested in looking at the temperature of the buildings, and so the background objects such as the sky, ground, trees, cars, etc. need to be removed. This will allow for a more accurate analysis in further processing when identifying the average temperature of each face of a building, as well as hotspot detection.

While automating the masking process for images with unwanted obstructions, we found there is no standard procedure to automatically detect and remove unwanted portions of images without some human input to guide the process of identifying proper portions desired for removal. As such, an effort was put forth to identify methods that worked without additional input in particular scenarios, and to quantify the accuracy of desired removal, which will be discussed in future sections. The remaining sections are divided as follows: *section 2*: Literature Review, *section 3*: Methods, and *section 4*: Conclusion and Future Work.

II. LITERATURE REVIEW

The current state of research concerning building detection in static 2D images primarily focuses on detection of buildings in wide field aerial images using roof features, while research involving detection of specific building features from terrestrial imaging (including drone imaging from heights relatively equal to that of the building) is much more sparse [8]. Additionally, much of the existing research found yielding successful results often requires prior knowledge of building features, such as model of window used, distance measurements or specific requirements for taking images such as standardized distance from faces and particular angles [8, 9].

This lack research on automated methods for background removal has motivated us to find a method that approaches full automation. There are some methods that show potential, such as the adaptive boosting (Adaboost) framework [8] and simultaneous imaging of infrared and visible wavelengths [1], which may benefit from combination with current image processing techniques such as feature detection and color isolation, warranting an investigation to measure their performance.

III. METHODS

While analyzing an image, it becomes necessary to disregard segments of the image that interfere with certain analysis procedures. One simple example of this 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 includes 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. The method this work is currently investigating is removal of unwanted portions of an image prior to analysis to make calculations more accurate. Two methods have shown to be useful in this process, with differing success in particular scenarios. These are edge detection and Dominant Color Isolation (DCI).

In order to measure the accuracy of these methods, we need to compare both the Canny based edge detection and DCI background subtraction with an ideal background subtraction and measure the difference. An ideal background subtraction is found by manually cropping the building by hand. From here, we can determine which pixels were treated incorrectly by each automated method. There are two types of errors that the algorithm can make: it can mistakenly remove a pixel that belongs to the building, or it can fail to remove a pixel that was part of the background. We use two metrics to measure the accuracy of the background subtraction based on the two types of errors described above: false positives, defined by:

$$\text{False positives} = \frac{\text{Pixels incorrectly removed}}{\text{Total number of pixels}} \quad (1)$$

and false negatives, defined by:

$$\text{False negatives} = \frac{\text{Pixels incorrectly remain}}{\text{Total number of pixels}} \quad (2)$$

By comparing the automated methods with the ideal background subtraction, we can record the number of pixels that are part of the building but were incorrectly determined to be background by the algorithm (denoted false positives) and the pixels

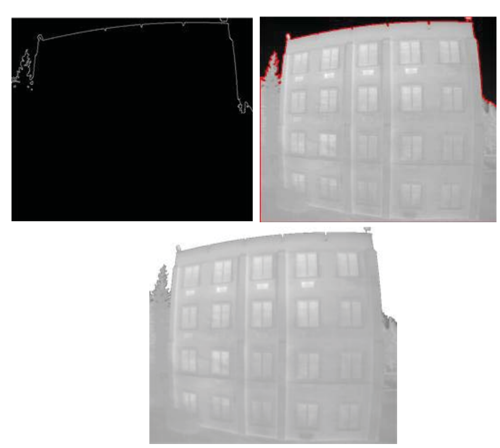

Fig. 1 Edge detection fails to eliminate background where there are no clearly defined edges

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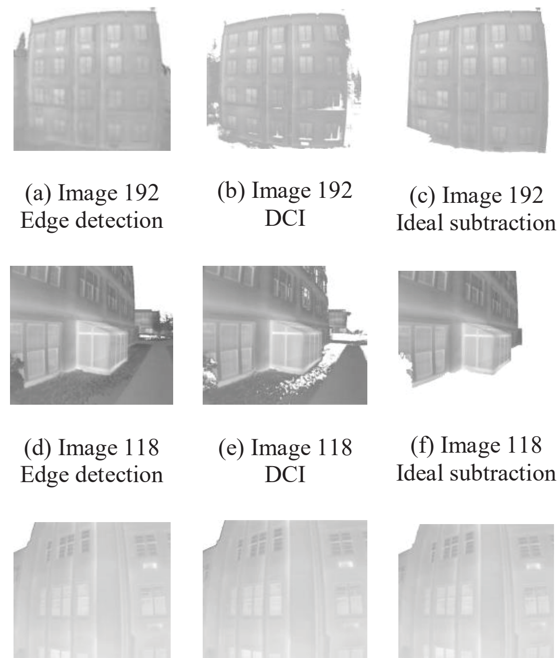
TABLE I
ACCURACY OF CANNY METHOD

Image #	False positives (%)	False negatives (%)	Total error (%)
192	$\frac{370}{327680}$ (0.11%)	$\frac{44654}{327680}$ (13.63%)	$\frac{45024}{327680}$ (13.74%)
118	$\frac{2}{327680}$ (0%)	$\frac{110132}{327680}$ (33.61%)	$\frac{110134}{327680}$ (33.61%)
168	$\frac{0}{327680}$ (0%)	$\frac{198}{327680}$ (0.06%)	$\frac{198}{327680}$ (0.06%)

which are part of the background but were incorrectly determined to be part of the building (denoted false negatives). The fewer false positives or false negatives, the more accurate the algorithm is at removing the background. This will quantify the accuracy of each method.

A. Canny Edge Detection

Edge detection operations are essentials components in a wide range of applications, such as image segmentation, pattern recognition, feature extraction, motion detection, or texture analysis. Canny's algorithm represents one of the most accurate edge detection methods. Edge detection methods have improved in recent years and taking advantage of these advancements has allowed for quick and simple solutions to basic problems in the background elimination process. The edge detection method applied uses first-order directional *Gaussian derivatives* to find edges by linking high-gradient pixels. Quality of edge detection can be altered by choosing a different process to detect edges, such as *first-order derivatives* of exponentials or binomial generalization of Sobel masks [10]. Finding the best methods and parameters for each image can be tedious task, and comes without the promise of substantial improvements of results, thus encouraging the investigation of automating this process; however, this is beyond the scope of this paper, and the results presented used a typical Canny method



(a) Image 192 Edge detection
(b) Image 192 DCI
(c) Image 192 Ideal subtraction
(d) Image 118 Edge detection
(e) Image 118 DCI
(f) Image 118 Ideal subtraction
(g) Image 168 Edge detection
(h) Image 168 DCI
(i) Image 168 Ideal subtraction

Fig. 2 Comparison of background subtraction methods

with a pixel range parameter set to two. Canny edge detection is a technique to extract useful structural information from different vision objects and dramatically reduce the amount of data to be processed [11]. The Canny edge detector [12] is a very popular edge operator, which is widely used in digital image processing, including remote sensing image processing. The Canny operator works in four stages: Firstly, the image is smoothed by Gaussian convolution. Secondly, a 2-D first derivative operator is applied to the smoothed image to calculate the gradient magnitude and direction. Thirdly, the process of non-maximal suppression (NMS) is imposed on the gradient image. Finally, the edge tracking process exhibits hysteresis controlled by two thresholds [13].

Edge detection performs well in areas where images contain distinct differences in separate regions, such as the boundary between the sky and other objects in the image, illustrated in Figure 1. Although this method works well for the upper portion of the image where the regions are distinct, it clearly does not detect the edges on the remaining sides of the building face, requiring a different method to separate these regions.

TABLE 2
ACCURACY OF DOMINANT COLOR ISOLATION METHOD FOR VARIOUS IMAGES

Image #	False positives (%)	False negatives (%)	Total error (%)
192	$\frac{13620}{327680}$ (4.16%)	$\frac{23555}{327680}$ (7.19%)	$\frac{37175}{327680}$ (11.34%)
118	$\frac{2316}{327680}$ (0.71%)	$\frac{90030}{327680}$ (27.48%)	$\frac{92346}{327680}$ (28.18%)
168	$\frac{0}{327680}$ (0%)	$\frac{99}{327680}$ (0%)	$\frac{99}{327680}$ (0%)

The accuracy of the DCI method is summarized in Table 1. It is observed that when analyzing Image 192, the edge detection algorithm has very few false positives (FP) as compared to the number of false negatives (FN). This means that the algorithm is accurate at removing pixels that should be removed, but it is not as reliable at removing pixels that it should be removing. This is also reflected in Figure 2, which shows a comparison of the resulting images from each background subtraction method. We can confirm from these images that the edge detection method results in very few FPs but high FNs We see that this method works best at eliminating the sky, but fails to eliminate the trees and the ground. Image 118 is an example when the edge detection method produces bad results. We observe again that this method produces very few FPs, but high FNs. Referencing Figure 2, we can see that the edge detection method correctly removes the sky, but it does struggle to remove bushes, grass, trees, the ground, and the other building seen in the background of the image. We can see that the error for this image is much higher because the background contains very little sky, and mostly consists of the ground and trees, which this method struggles to remove. Image 168 is an example where the edge detection method works very well. Because the background consists of only the sky, a feature that edge detection works well at removing, and contains no other features such as the ground or trees, the error for this image is very low.

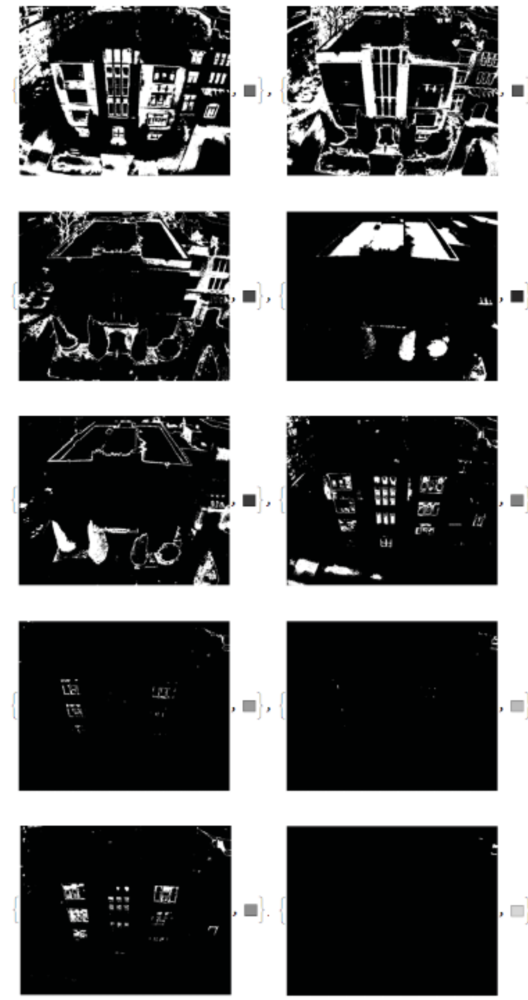


Fig. 3 Dominant Color Isolation

B. Color Isolation Masking

With color isolation masking, the goal is to separate the image into dominant color channels, while masking the remaining colors. This is done by taking an image, and computing the "distance" between colors, where the distance between two colors is computed as the Euclidean distance between the two color vectors in the LABColor space, where L is the lightness or approximate luminance, A is the first color parameter, green (negative) to magenta (positive) and B is the second color parameter, blue (negative) to yellow (positive) forming the vector {L,A,B}, and A,B are in the range of ± 1. Once the distance has been specified, colors with a distance less than a set threshold are clustered, and clusters are separated, and masks are created by binarizing the image, with any color in the cluster appearing white, and all other colors appearing black. This results in a set of masks corresponding to the distinct color clusters. An example of this process can be seen in Figure 3. With these masks, it is possible to combine certain masks in order to eliminate background objects, while the building remains.

To measure the accuracy of the DCI method, we will compare the DCI background subtraction to an ideal subtraction. A summary of the results from this comparison is shown in Table 2. We see that the DCI method produces results with comparable error to the edge detection method. Similarly to edge detection, DCI produces fewer FPs than FNs in all three cases. Comparing Tables 1 and 2, we see that the total error rates using DCI on Image 192 was slightly lower than the edge detection method, and the number of false positives was lower using edge detection. Looking at Image 118, we see that DCI has more FPs but fewer FNs. In summary, DCI performs better on this image than canny edge detection. In the final example, looking at Image 168 we see that both DCI and edge detection perform the same with returning no FPs, but DCI returns fewer FNs. Overall, DCI has a more accurate background removal on this image.

IV. CONCLUSION AND FUTURE WORK

The paper investigated pre-processing of thermal imagery data sets from unmanned aerial vehicles for energy audit applications. Specifically, a Canny edge detection and a DCI approach were compared for accuracies. Overall, DCI outperforms edge detection with all three images. However, it is important to note that edge detection returns fewer false positives as an overall trend. Although DCI appears to be superior, and perform sufficiently well in certain situations such as identifying complex objects that are similar in {L, A, B} space. On the other hand, it does give false positives (FP) in some other conditions that may result in loss of desirable information, and should be avoided.

In the future we plan to combine these two methods, as well as automate the mask selection process. With DCI, automatically creating a set of masks from all possible combinations of output masks then minimizing the errors should result in optimal outcomes with full automation, and should serve as a starting point for additional processing methods.

VI. ACKNOWLEDGEMENT

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