Application of fuzzy logic in isothermal surface boundary determination

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Abstract

Determining the space of the isothermal surface in everyday use of the thermal imaging camera represents an intuitive process in which the aim is to immerse the IFOV as much as possible into the analyzed domain to achieve accurate readings. When using an accessible low-resolution camera, the challenge becomes greater as the image that the camera displays is of higher resolution than the sensor information. Furthermore, camera image is often interpolated or superimposed on the visual image to achieve better detail detection. The aim of this paper is to demonstrate application of fuzzy logic in determination of isothermal surface edge on the example of active black body surface. Using a camera with a resolution of 320x240 NETD 45 mK, a black body with a temperature of 60°C was recorded and a detailed analysis of its surface was carried out. Fuzzy logic is used to determine the edges of the image by assigning each pixel a degree of edge membership, instead of simply classifying pixels as edge or non-edge. This method allows for better ambiguities and noise management in the image, resulting in smoother and more precise edges. Hence, fuzzy logic represents an excellent method for determining edges in situations with low resolution.

1. Introduction

Infrared thermography (IRT) is a non-contact technique that measures temperature distribution of objects based on their infrared radiation. It has been widely used for condition monitoring and fault diagnosis of electrical equipment, as well as for research and development of thermal processes [1]. One of the challenges of IRT is to detect edges of an objects in the infrared images, which are often blurred or noisy due to the limitations of the infrared camera and certain environmental factors. Edge detection is important for segmenting the regions of interest, measuring temperature gradients, and identifying anomalies in infrared images [2]. For research purposes, isothermal surface of black body Voltcraft IRS-350 was used, figure 1 [3]. IRS-350 has an active surface, unlike some other black body models as [4].

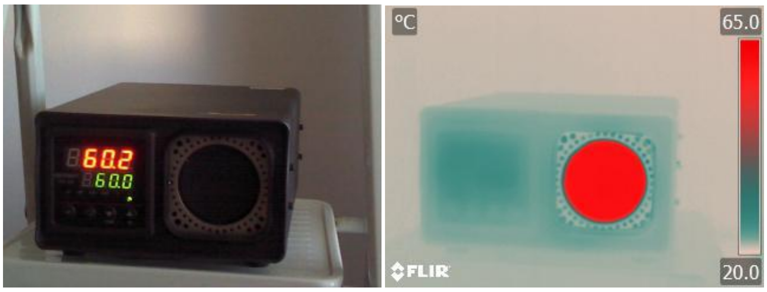

Fig. 1. *Thermogram isothermal surface of the IRS-350 black body.*

Table 1. *Black body specification.*

Black body type	Voltcraft IRS-350
Temperature range	50 °C to 350 °C
Accuracy	±0.5 °C at 100 °C, ±1.2 °C at 350 °C
Stability	±0.1 °C at 100 °C, ±0.2 °C at 350 °C
Emissivity of measuring area	0.95
Operating temperature	5 °C to 35 °C

The basic characteristics of the black body under study are shown in table 1, whereas characteristics of used thermal camera Flir E60bx are shown in table 2. Registered temperature values during the calibration control are presented in table 3.

Table 2. *Specification of used Infrared thermal camera.*

Specifications	Flir E60bx
IR resolution	320 × 240
NETD	45 mK
FOV	25° × 19°
IFOV	1.36 mrad
Spectral range	7.5–13 µm
Temp. range (°C)	−20 to + 120
Accuracy (°C) or (%) of reading	±2 °C or ±2% for ambient temperature 15 °C to 35 °C

Table 3. *Registered temperature values during the calibration process.*

IRS-350 Blackbody (°C)	FLIR E60bx	difference
50	50.7	0.7
60	60.5	0.5
70	70.6	0.6
80	80.8	0.8
90	90.6	0.6
100	101.0	1.0
110	110.8	0.8
120	121.0	1.0
130	131.0	1.0
140	141.0	1.0
150	>150	

Relatively low resolution of the thermographic record enables the processing of CSV data in Excel, as seen in figure 2. Using condition formatting of individual cells and adjusting color scales in Home tab with careful selection of colors, a look that is similar camera palettes can be approached. Excel can be used for basic analysis, and even to show distribution in a three-dimensional view as in figure 3 and figure 4.
However, if one needs to determine the geometry, Excel is no longer applicable, as seen in figure 5. The main problem is that Excel is a table calculator which reduces the pixel level to the dimensions of table cells containing numerical values. Note that figure 2 and figure 5 have undergone image processing to bring the proportions to realistic values. This approach can only be applied to thermograms of lower resolution as higher resolution represents a processing problem for Excel.

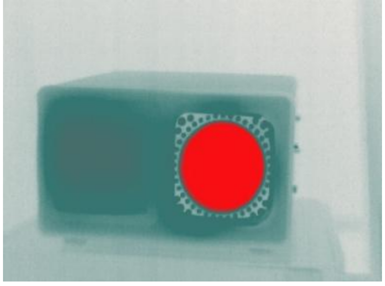

Fig. 2. *Thermogram generated by MS Excel from CSV data.*

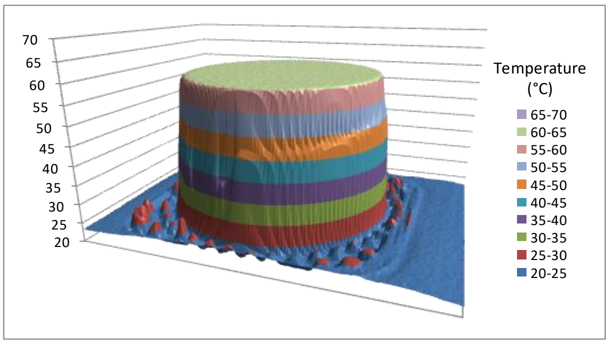

Fig. 3. *Active black body surface shown in 3D Excel view.*

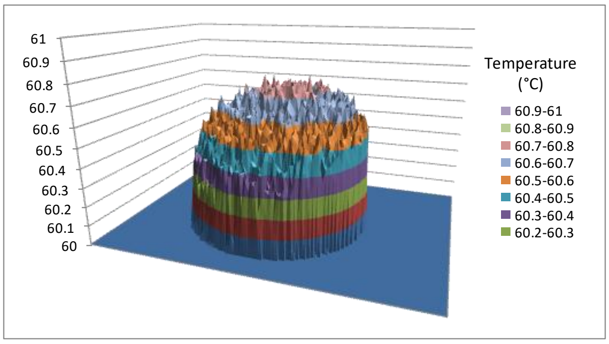

Fig. 4. *3D active black body surface in a narrow interval of registered temperatures.*

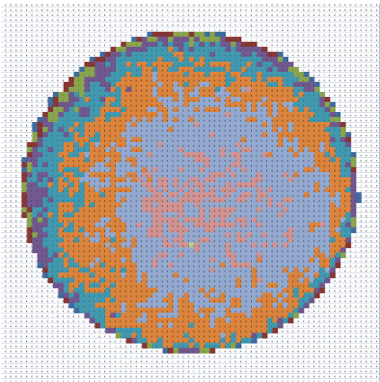

Fig. 5. *Temperature distribution over the surface of the active surface.*

Low-resolution infrared images often arise due to constraints in sensor technology, limited pixel count, and need for real-time applications. The consequences of such limitations are particularly pronounced when attempting to discern fine details or subtle temperature variations within a scene. This inadequacy can impede identification of critical hotspots in electrical components, detection of minute structural defects in materials, or precise characterization of thermal anomalies in medical applications. This paper explores the intersection of infrared imaging, low-resolution challenges, and the application of cutting-edge detection algorithms. By delving into the intricacies of image processing techniques [5], we propose innovative solution that not only mitigate the limitations imposed by low spatial resolution, but also pave the way for more accurate and insightful thermal analysis across diverse domains. By analyzing the surface of the black body in a narrow interval of registered temperatures, challenges of our analysis can be easily visualized (figure 2.).

2. Related work

Several methods have been proposed for edge detection of infrared images, which can be classified into two categories: traditional methods and deep learning methods. Traditional methods are based on mathematical operators or filters that enhance the edges by computing the derivatives or differences of the pixel intensities. Some examples of traditional methods are Sobel, Canny, Roberts, Prewitt, Laplacian of Gaussian (LoG), and Difference of Gaussian (DoG). These methods are simple and fast, but they may fail to detect weak or complex edges, or produce false edges due to noise or illumination variations, as shown in figure 6.

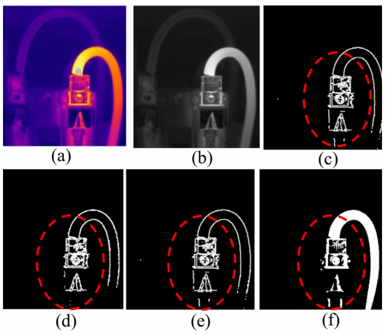

Fig. 6. *Identification of a hotspot area picture in grayscale: (a) RGB image, (b) grayscale image, (c) using Prewitt, (d) using Roberts, (e) using Sobel, (f) using Otsu [7].*

Moreover, they require manual tuning of parameters or thresholds to achieve optimal results [6]. Various edge detection methods, such as Sobel, Canny, Roberts, and Prewitt, are employed in image processing to emphasize boundaries and detect intensity variations. The Sobel operator involves two 3x3 convolution kernels for horizontal (G_x) and vertical (G_y) gradients:

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, \quad G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \tag{1}$$

The gradient magnitude (*G)* is then calculated as $\sqrt{G_x^2 + G_y^2}$. The Canny edge detector, a multi-stage algorithm, involves Gaussian smoothing, gradient computation (often using Sobel operators), non-maximum suppression, and hysteresis-based edge tracking. The Roberts Cross operator uses a pair of *2x2* convolution kernels for gradient calculation:

$$G_x = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}, \quad G_y = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \tag{2}$$

The gradient magnitude (*G*) is computed similarly. The Prewitt operator, similar to Sobel, uses convolution kernels for gradient computation:

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}, \quad G_y = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix} \tag{3}$$

These equations highlight the mathematical operations involved in these edge detection techniques, providing a foundation for image analysis in computer vision applications. The Otsu method is an automatic image thresholding technique aiming to find the optimal threshold (t_{opt}) that separates an image into foreground and background. It maximizes the ratio of between-class variance (σ_B^2) to within-class variance (σ_W^2). The objective function $\sigma(t)$ is defined as:

$$\sigma(t) = \frac{\sigma_B^2(t)}{\sigma_W^2(t)} \tag{4}$$

and the optimal threshold is found by iterating through possible thresholds and selecting the one that maximizes $\sigma(t)$.The image is then segmented based on pixel intensities relative to the optimal threshold. Otsu's method provides an efficient way to automate image thresholding for tasks such as object segmentation.

Deep learning methods are based on neural networks that learn the features and patterns of the edges from a large amount of labeled data. Some examples of deep learning methods are Holistically-Nested Edge Detection (HED) [8], Deep Contour-Aware Network (DCAN), Richer Convolutional Features for Edge Detection (RCF), and Deeply Supervised Salient Object Detection with Short Connections (DSS). They operate on the principle of utilizing neural networks to learn intricate features and patterns associated with edges from extensive labeled datasets [9], as illustrated in figure 7.

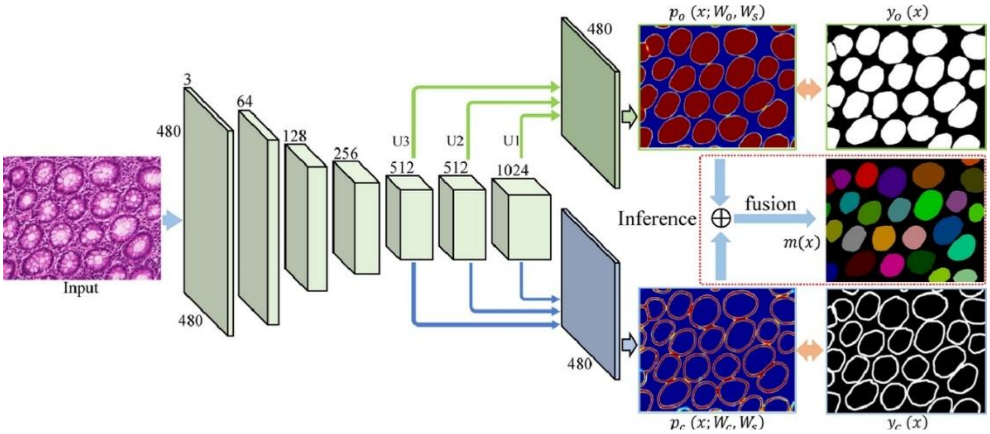

Fig. 7. *Neural network architecture for image segmentation and edge detection [9].*

HED, for instance, focuses on predicting edges at multiple scales through a deep neural network with side outputs at various layers. DCAN improves contour detection by integrating a contour-aware module into the network architecture. RCF emphasizes the importance of richer convolutional features and employs dense skip connections to refine features at different scales. DSS, originally designed for salient object detection, enhances information flow through short

connections, facilitating the capture of fine and coarse details crucial for edge detection. These methods are trained on datasets with images and corresponding labelled edges, utilizing specific loss functions to guide the learning process. Overall, they outperform traditional edge detection techniques by automatically learning hierarchical representations of features from diverse data.
Deep learning methods can achieve better performance and robustness than traditional methods, as they can capture high-level semantic information and handle complex scenarios (one such can be seen on figure 8). However, they also have some drawbacks, such as requiring a large amount of annotated data, high computational cost, and lack of interpretability [10].

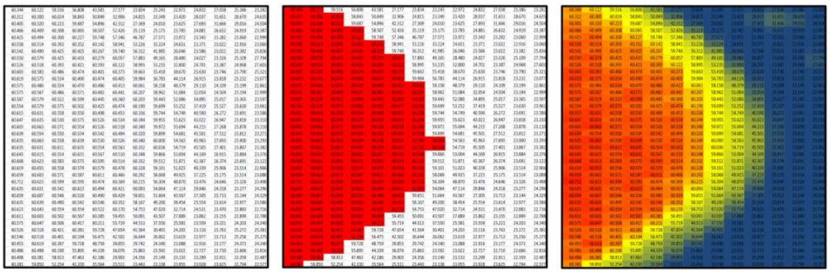

Fig. 8. *The challenge of determining the edge of an isothermal surface.*

3. Radiometric data and fuzzy logic

Radiometric data is a valuable source of information for various fields of study, such as geology, archaeology, and climatology. However, the accuracy of radiometric data depends on the resolution of the measurement devices and the methods used to analyze the data. Low resolution can introduce errors and uncertainties in the radiometric data, especially for the border cases where the measured values are close to the detection limits or the calibration standards.

Fuzzy logic, conceived by Lotfi Zadeh in the 1960s [11], is a mathematical framework designed to address reasoning and decision-making in the presence of uncertainty. Departing from the strict binary nature of traditional logic, fuzzy logic introduces the concept of membership functions that assign degrees of truth to variables between 0 and 1. Fuzzy sets, collections of elements with gradual membership, play a central role. Fuzzy rules, expressed in "if-then" statements, define relationships between input and output variables, considering the degree of membership. The fuzzy inference system applies these rules to determine the degree of membership of the output variable, allowing for a nuanced representation of uncertainty. Defuzzification can then be employed to convert the fuzzy set result into a specific numerical value if a crisp output is required.

Fuzzy logic is a type of logic that deals with uncertainty and imprecision. Unlike classical logic, which only allows for true or false values, fuzzy logic can assign degrees of truth to propositions, such as "very true", "somewhat true", or "not very true" [12]. Therefore, fuzzy logic has various applications, including control systems, decision-making, pattern recognition, and artificial intelligence, where it offers an approach for handling imprecision and vagueness in complex problem-solving scenarios.

4. Results

In this paper, we present a comprehensive exploration of the use of edge detection in image processing as a strategic approach to tackle the challenges posed by low spatial resolution in infrared imaging. Our primary objective is to demonstrate how advanced edge detection techniques can effectively enhance the perceptual clarity of low-resolution infrared images, providing a more accurate representation of temperature variations and spatial details. Figure 9 shows the edge detection of the black body region of interest.
Figure 10 to figure 13 represent more detailed look of the edge detection using fuzzy logic with represented membership function and zoomed in ROI.

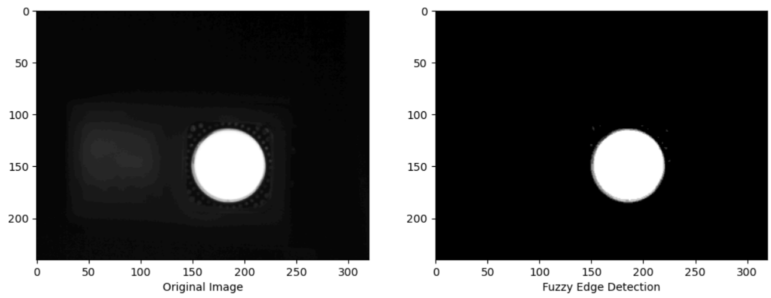

Fig. 9. *Original IRT image and edge detection ROI.*

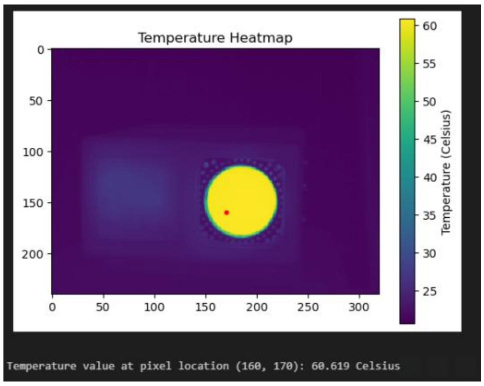

Fig. 10. *Evaluation of the correct readings.*

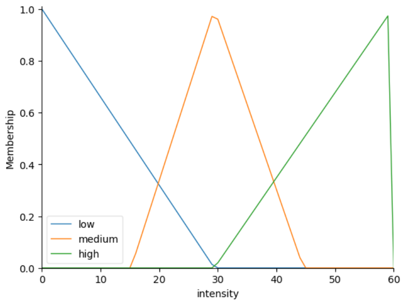

Fig. 11. *Fuzzy logic membership function via intensity readings.*

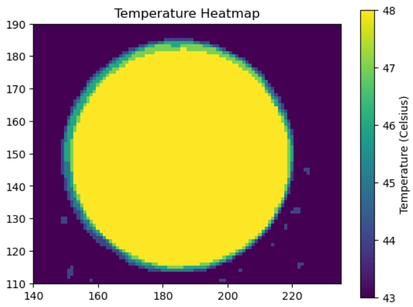

Fig. 12. *Zoomed in region of interest.*

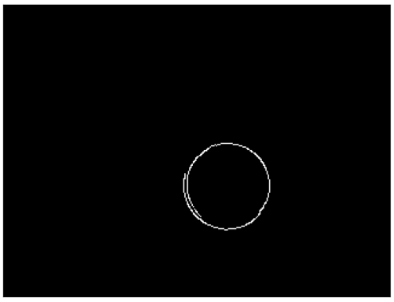

Fig. 13. *Detected edges of isothermal surface*

5. Conclusion

In this paper, a novel method for estimating the error margin of image processing algorithms based on edge detection was presented. Theoretical background and the practical implementation of approach was explained, and we evaluated its performance on various datasets. We showed that our method can provide reliable and accurate estimates of the error margin, which can be used to improve the quality and robustness of image processing applications.

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