IMAGE SEGMENTATION PROCESSING FOR THERMOGRAPHIC ANALYSIS

Ivana Walter (Student),
Marko Tanasković (Mentor)*

Singidunum University,
Belgrade, Serbia

Abstract:

Thermography is commonly applied for determining abnormalities in various systems. Thermal image analysis can identify different issues on objects. Infrared inspection has wide application in various fields such as medicine, electrical engineering, and construction. The images in this technology are obtained by colouring using pseudo-colours that correspond to the radiative energy of detected items. The infrared detector registers surface temperatures in the surrounding and maps them to the corresponding colours according to the specific colour palette. This paper presents methods that can be applied in the processing for thermal images in order to simplify the inspection of temperature levels.

Keywords:

infrared, image segmentation, neural network.

INTRODUCTION

Due to the increases in computational power and available datasets, todays CNNs can overperform normal visual capabilities. They are applied in many areas e.g., self-driving cars, automatic video classification, voice recognition, natural language processing.

Image segmentation represents the division of images according to different classes of objects where classification is represented by different colours. Convolutional Neural Network (CNN) is commonly applied in image segmentation as it detects objects by extracting specific characteristics from the image, that are then classified and differentiated on pixel basis. [1]

Figure 1 represents the principle of Convolutional Neural Network CNN operation that is similar to the visual cortex. Neurons in the first convolutional level process defined small segments of the input image. Neurons in subsequent layers are associated with limited groups of neurons from the previous layer.[2] The first level extracts low level features e.g., shapes and curves and following layers process high-level features. In the convolution stage various filters can be applied in order to obtain the feature map.

Correspondence:
Marko Tanasković

e-mail:
mtanaskovic@singidunum.ac.rs

DOI: 10.15308/Sinteza-2022-394-398

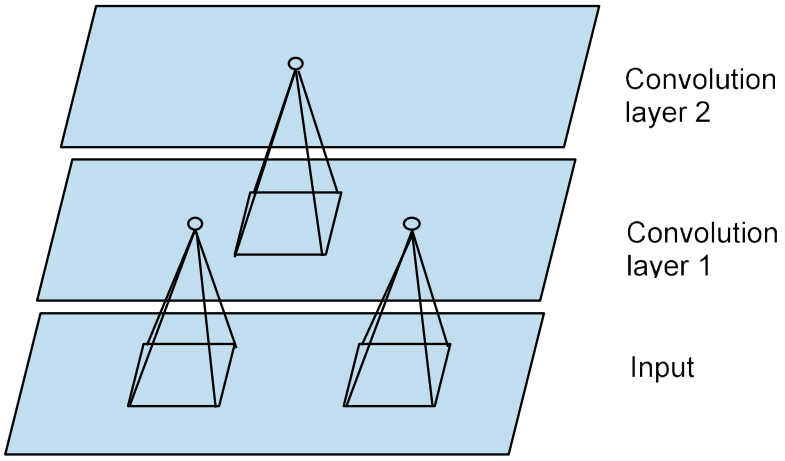

Figure 1 – CNN principle

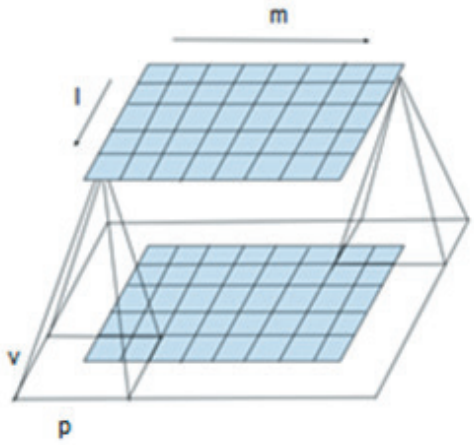

Figure 2 – Operation between layers

In the pooling stage the image dimensions are reduced commonly by taking the average or the maximal values from the defined regions, that enables obtaining smaller image representations.

The neurons from the second layer are connected to neurons from the previous layer where the receptive field is given by dimensions v and p as represented on Figure 2.

The Equation 1 represents the output function of the neural network that equals to the inputs from the previous network layers multiplied by the corresponding weighted factors.

$$f = \sum_{l}\sum_{m}\sum_{F} x_{l,m,F} w_{l,m,F} + b$$

Equation 1 – Output of neurons in convolutional layers

where f is the output from the CNN in the position l, m on the convolutional layer for the feature map F that represents the number of feature maps from the previous layer, x represents the input sequences, w stands for corresponding weighted sums for those inputs, and b is bias value.

2. RELATED RESEARCH

Hespeler et al. [3] provide the brief overview of various algorithms for object detection including their accuracy comparison. Arjoune et al. [4] propose combined image segmentation with heat loss quantification for inspecting building thermal performance. In [5] the authors represent the detailed thermography principles and non-destructive tests.

3. METHODOLOGY

If specific image segments can be isolated, the specific temperature of that segment can be determined, and the temperature differences of individual segments can be compared. One of the common methods for image segmentation is the Mask R-CNN. In this way, certain elements on the image can be isolated to avoid the influence of individual parts in the infrared analysis.

Mask R-CNN detector distinguishes pixels that belong to different items. It is based on the Faster R-CNN structure that uses the CNN to extract features. In this methodology more than 2000 anchor points are generated on the image as references for proposed regions where objects can potentially be registered. After predicting bounding boxes, the Mask R-CNN performs pixel-based classification. [6]

For more comprehensive analysis, the deeplabv3 model can be used that can efficiently differentiate global objects of interest. DeepLabv3 is composed using the ResNet-50 or ResNet-101 backbone. The DeepLab model relies on the Atrous convolutions and Atrous Spatial Pyrmid Pooling (ASPP) framework. In DeepLabv3 model the features are extracted from the backbone network, the ASPP network performs the classification of each pixel and finally the image is passed through the convolutional network to obtain the output image. [7]

In case when there are parallel visual images available that correspond to thermal images, the desired objects can be selected with corresponding bounding boxes using Faster R-CNN for the object detection on the visual image. The object can then be extracted from this region on the corresponding thermal image.

For precise separation of segments, the images can be processed by separating the contours. Contours are displayed with the near colour intensity, and it differentiates shapes across the image. Contours represent arrays of coordinates of object boundaries. In this way the desired shapes can be extracted from the image if the boundaries are provided.

4. RESULTS

The background can be extracted using the Mask R-CNN and DeepLabv3 in order to perform inspections on relevant regions. Figures 3, 4 and 5 represent the segmentation of the visual image with the deeplabv3 pretrained model that is then used for fine-tuned differentiation of relevant objects.

Figure 3 – Captured visual image

Figure 4 – Segmented thermal image with deeplabv3

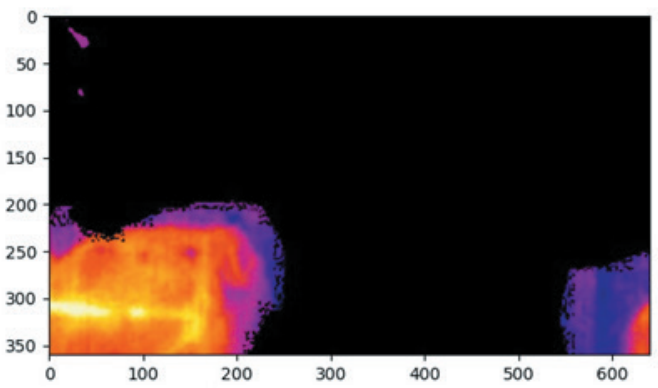

Figure 5 – Extracted items from thermal image

Figures 6 and 7 display the method for extracting the region by applying the object detector and then separating this area on the corresponding thermal image.

Figure 6 – Detection using Faster R-CNN

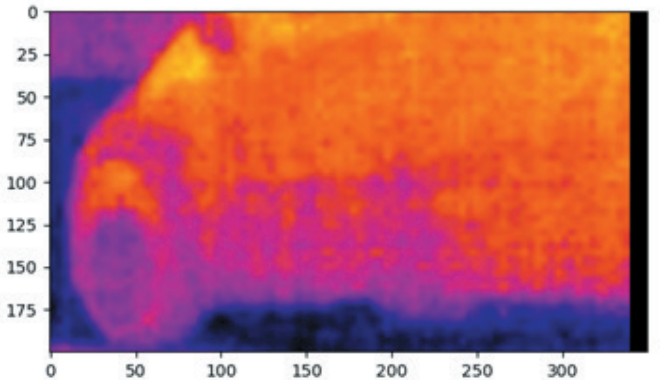

Figure 7 – Separated thermal region

5. CONCLUSION

Image processing of thermal captures can detect unusual characteristics in different systems. In order to facilitate the complex analysis of thermal images, image processing techniques based on AI can be used to draw special attention to the temperature characteristics of individual objects. This method should simplify the inspections of systems by focusing on smaller elements, specifically those characterized by higher temperatures that are displayed in light colours. However, thorough temperature analysis and improved methods are still required for qualitative thermal inspections.

6. ACKNOWLEDGEMENT

This research was supported by the Science Fund of the Republic of Serbia, Grant #6524745, AI-DECIDE.

7. REFERENCES

[1] N. Vlahović, N. Ilić and M. Stanković, "Deep Learning in Video StabilizationHomography Estimation," in *14th Symposium on Neural Networks and Applications,* Belgrade, 2018.

[2] A. Géron, Hands-on Machine Learning with Scikit-Learn, Keras & TensorFlow, O'Reilly, 2019.

[3] S. C. Hespeler, H. Nemati and E. Dehghan-Niri, "Non-destructive thermal imaging for object detection via advanced deep learning for robotic inspection and harvesting of chili peppers," 2021.

[4] Y. Arjoune, S. Peri, N. Sugunaraj, A. Biswas, S. Debanjan and P. Ranganathan, "An Instance Segmentation and Clustering Model for Energy Audit Assessments in Built Environments: A Multi-Stage Approach," *Sensors (Basel)*, no. 21(13):4375. doi: 10.3390/s21134375., 2021 Jun 26.

[5] R. Usamentiaga, P. Venegas, J. Guerediaga, L. Vega, J. Molleda and F. G. Bulnes, "Infrared Thermography for Temperature Measurement and Non-Destructive Testing," *Sensors (Basel).*, no. 14(7): 12305–12348., 2014 Jul.

[6] M. Tanaskovic and I. Walter, "Object recognition in the dark with image segmentation," in *ETIKUM*, Novi Sad, 2021.

[7] L.-C. Chen, G. Papandreou, F. Schroff and A. Hartwig, "Rethinking Atrous Convolution for Semantic Image Segmentation," *ArXiv*, no. abs/1706.05587, 2017.