

Proceedings

Concept of Computer Vision Based Algorithm for Detecting Thermal Anomalies in Reinforced Concrete Structures [†]

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- Presented at the 15th International Workshop on Advanced Infrared Technology and Applications (AITA 2019), Florence, Italy, 17–19 September 2019.
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Published: 21 September 2019



Abstract: In Hong Kong, there is great abundancy of aged buildings and infrastructures for which a re-assessment of the current status is needed. Water exfiltrations/infiltrations, deteriorating insulations, thermal bridges and regions of failure are among the most recurrent symptoms to be found in existing Reinforced Concrete (RC) structures. Diagnosis of such symptoms, in the form of thermal infrared anomalies, is usually performed through infrared (IR) image capturing, followed by qualitative assessment. This paper presents a novel automated computer-vision-based method for detecting thermal anomalies. Such Computer-Vision (CV) algorithm is tested on different thermal scenarios including beam elements, roofs and entire façades of RC buildings. Thermal anomalies related to cases of water leakages, moisture trapping and debonding are successfully detected. The authors intend to undertake further research for successfully implementing the method for detecting also other thermal dissimilarities.

Keywords: AI; Civil Engineering; computer-vision; drone; infrared; reinforced concrete; thermography; water leakage

1. Introduction

Assessment of the status of RC buildings in urban areas has become an important research field in the last few years. Tools such as IR cameras can be used for evaluating thermal scenarios and perform structural analyses. Pairage of Unmanned Aerial Vehicles with IR cameras enable professionals to obtain outstanding captured IR photographs and video recordings. Nowadays, the popularity of usage of drones for building inspections is consistently on the rise due to the great advantages provided in terms of safety, operation, cost and efficiency. Additionally, through UAV, unique aerial perspectives can be captured and inaccessible areas can be reached [1]. Furthermore, UAV have no impact on the environment and they provide more accurate data [2,3]. A research work on automated detection of thermal heat losses in proximity of windows was proposed by Martinez-De Dios and Ollero [4]. Heat-losses areas were tracked according to a fixed threshold of 7 °C. However, such approach may be prone to infeasibility and errors according to weather conditions and building materials. A more comprehensive approach utilising thermographic automation was introduced by Mauriello and Froehlich [5]. In a later research paper, Mauriello et al. highlighted the challenges and problems related to automation, data quality and technical feasibility [6].



This paper documents the ongoing research, jointly operated by RaSpect Intelligence Inspection Ltd. and Infrared Engineering & Consultants Ltd., on a novel automated CV-based algorithm for detecting thermal anomalies in RC buildings.

2. Prior Considerations

Thermal data are sensitive to weather conditions. Climatic factors such as rain, heavy wind and snow can considerably affect the outcome of an IR inspection. Moreover, they may not be the appropriate conditions for flying a drone. Other environmental factors, such as solar radiation, cloud coverage, wind speed, humidity etc. can affect the external surface temperature. Through a series of test flights and a literature study, Entrop and Vasenev developed a protocol for usage of IR-UAVs in the construction domain [7]. Such recommendations are taken as reference for ensuring high quality of data.

3. CV Algorithm

The algorithm target is to identify regions of thermal anomaly in an automated fashion. Such anomalies are usually detectable in the form of sharp changes in temperature, hotter or colder according to heat transfer processes in different seasons. The CV-based algorithm is comprehensive of the following four stages:

1. **Initial Model Calibration:** Thermal images (see sample in Figure 1) are post-processed in the form of two-dimensional matrices, where each cell (representative of a pixel) is associated to a temperature value. According to a tentative initial Bin Width (BW), the histogram shown in Figure 2 is obtained. The histogram is likely to show tendency toward cold or hot regions in distinct materials with different thermal capacitance according to the season. As first assumption, in case the histogram has a cold tendency, an Anomaly Bin (AB) and an Opposite Bin (OB) are initially defined as coldest and hottest bin, or viceversa in a hot scenario. Accordingly, an Anomaly Threshold (AT) (represented with a red line in Figure 2) is defined for temperatures 'entering' the AB. BW, AB, OB and AT are key parameters of the algorithm. A dynamic calibration procedure for such variables is introduced as follows.



Figure 1. IR image of a beam with evident water leakage.



Figure 2. Histogram of thermal data extracted according to Figure 1.

- 2. **Dynamic Calibration:** Let *n* be the total amount of bins in the histogram of pixels of a thermal image, then AT, AB and OB are adjusted by filtering off eventual false positives. The three operations leading the dynamic calibration are listed in the following:
 - It is assumed that if the amount of pixels in the OB is less than a significance lower bound α , then such data are probably irrelevant particulars and they are filtered off. Accordingly, the AT is shifted by BW and the neighbour bin becomes the 'new OB'. Such procedure is repeated until the condition OB $\geq \alpha$ is satisfied.
 - It is assumed that if there is more than one pixels peak in the histogram, then the pixels distribution still contains irrelevant information which may lead to false positives (such as background sky). In such case, it is very likely that relevant information are lying at mid-range temperatures. Eventual irrelevant peaks (with an amount of pixel not exceeding 10% of the total pixels) and their bounding pixels are filtered off.
 - It is assumed that if the amount of pixels in the AB is greater than a significance upper bound *β*, then *n* and BW are not adequate, therefore *n* is increased by a pre-defined growth ratio and BW decreases accordingly. The overall calibration is repeated until the condition AB ≤ *β* is satisfied.

The dynamic calibration changes the configuration of data shown in Figures 1 and 2 to the one displayed in Figures 3 and 4. It is now clear that the amount of data has been significantly lowered and relevant data are not discarded.



Figure 3. Filtered IR image of the beam shown in Figure 1 after dynamic calibration.



Figure 4. Histogram of thermal data extracted according to Figure 3.

3. **Identification of Thermal Edges:** In this stage of the algorithm, thermal edges are identified using a Canny edge detector [8], obtaining the results shown in Figure 5. Irrelevant thermal edges are filtered off using Otsu Thresholding Method on a gray-level histogram [9], and the results are displayed in Figure 6. Evidently all irrelevant thermal edges are filtered off whilst the edges defining the contour of the beam and regions with sharp changes in temperature are not discarded.



Figure 5. Thermal edges derived through Canny's edge detector.



Figure 6. Thermal edges after Otsu's Thresholding on gray-level histogram.

4. Leakage segmentation: Leakage will lie somewhere close to the identified thermal edges. Regions of water leakage are identified as follows. A neighborhood relationship is derived for establishing top, bottom, left and right neighbour pixels of each single pixel [10]. A Neighbours Size (NS) is assumed for defining the domain of existence of leakage around thermal edges (see Figure 7). Data is then filtered off according to the adjusted value of AT obtaining results as shown in Figure 8. In such figure it is clear that a thermal anomaly related to water leakage has been successfully detected.



Figure 7. Filtered IR image of the beam shown in Figure 1 after dynamic calibration.



Figure 8. Final output in terms of detected thermal anomalies.

4. Case Studies

Inspection results for other thermal images are shown as follows.

Figure 9 illustrates the case of a beam with small symptoms of water leakage, not clearly detectable through the IR image. In such case, a large amount of pixels include background sky containing irrelevant informations. As displayed in Figure 10, the proposed CV algorithm was capable of successfully filter off the sky and identify the thermal anomaly.

A case of a roof, seen from above, with evident symptoms of debonding of roof substrates caused by previous water infiltrations or waterproofing layer delamination is shown in Figure 11. In this thermal scenario, differently from the other cases, the thermal anomalies lie in a mid-range temperature. The results of the CV algorithm (see Figure 12) show the target area was successfully detected along with a small region of false positives in the upper part of the figure.

Figure 13 shows an IR image of a portion of façade of a residential building. Windows, air conditioners and other elements can clearly be distinguished due to thermal differences provided

by different materials. However, as shown in Figure 14, the CV algorithm does not detect any false positives and does not return any thermal anomaly.



Figure 9. IR image of a beam with non-evident water leakage including large portion of noise caused by background sky.



Figure 10. Final output in terms of detected thermal anomalies for the case of Figure 9.



Figure 11. IR image of a roof presenting symptoms of debonding.



Figure 12. Final output in terms of detected thermal anomalies for the case of Figure 11.



Figure 13. IR image of a façade with no evident symptom of debonding of roof substrates.



Figure 14. Final output in terms of detected thermal anomalies for the case of Figure 13.

5. Conclusions

This paper presents framework and numerical applications of a CV-based algorithm for detecting thermal anomalies in RC buildings jointly developed by RaSpect Intelligence Inspection Ltd. and Infrared Engineering & Consultants Ltd. The algorithm makes use of thermal imaging for inspecting RC buildings, and targets sharp anomalous changes in temperature. The algorithm has been tested for a set of thermal images, and some of the most significant applications are reported herein. The proposed solution aims at providing a valid alternative to costly and time consuming qualitative inspections of RC buildings. The developed approach allows for a fast yet accurate detection of areas of thermal

anomalies with broad industrial applicability. Future research work will be undertaken on further improving the existing solution for performing a diagnosis of the problem.

Funding: This research received no external funding

Conflicts of Interest: The authors declare no conflict of interest.

References

- Mavromatidis, L.E.; Dauvergne, J.-L.; Lunazzi, R.; Batsale, J.-C. First experiments for the diagnosis and thermophysical sampling using pulsed IR thermography from unmanned aerial vehicle (UAV). In Proceedings of the In 2014 Quantitative InfraRed Thermography Conference, Bordeaux, France, 7–11 July 2014; doi:10.21611/qirt.2014.213.
- 2. Grinzato, E. IR Thermography Applied to the Cultural Heritage Conservation. In Proceedings of the 18th World Conference on Nondestructive Testing, Durban, South Africa, 16–20 April 2012.
- 3. Harvey, M.C.; Rowland, J.V.; Luketina, K.M. Drone with thermal infrared camera provides high resolution georeferenced imagery of the Waikite geothermal area, New Zealand. *J. Volcanol. Geotherm. Res.* **2016**, 235, 61–69.
- Martinez-De Dios, J.R.; Ollero, A. Automatic Detection of Windows Thermal heat Loseses in Buildings Using UAVs. In Proceedings of the 2006 World Automation Congress, Budapest, Hungary, 24–26 July 2006; doi:10.1109/WAC.2006.375998.
- Mauriello, M.L.; Froelich, J.E. Towards Automated Thermal Profiling of Buildings at Scale Using Unmanned aerial Vehicles and 3D Reconstruction. In Proceedings of the 2014 ACM International Joint Conference on Pervaisve and Ubiquitous Computing: Adjunct Publication, Seattle, WA, USA, 13–17 September 2014; doi:10.1145/2638728.2638731.
- Mauriello, M.L.; Norooz, L.; Froelich, J.E. Understanding the Role of Thermography in Energy Auditing: Current Practices and the Potential for Automated Solutions. In Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, Seoul, Korea, 18–23 April 2015; pp. 1993–2002; doi:10.1145/2702123.2702528.
- 7. Entrop, A.G.; Vasenev, A. Infrared drones in the construction industry: designing a protocol for building thermography procedures. *Energy Procedia* **2017**, *132*, 63–68, doi:10.1016/j.egypro.2017.09.636.
- 8. Canny, J. A Computational Approach to Edge Detection. *IEEE Trans. Pattern Anal. Mach. Intell.* **1986**, *6*, 679–698, doi:10.1109/TPAMI.1986.4767851.
- 9. Otsu, N. A Threshold Selection Method from Gray-Level Histograms. *IEEE Trans. Syst., Man Cybern.* **1986**, *9*, 62–66, doi:10.1109/TSMC.1979.4310076.
- 10. De Filippo, M.; Kuang, J.S. Pseudo-lower bound method for assessing concrete slabs. *Proc. Inst. Civ. Eng. Struct. Build.* **2019**, doi:10.1680/jstbu.18.00130.



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