# ALGORITHMS FOR THE AUTOMATIC DETECTION AND CHARACTERIZATION OF PATHOLOGIES IN HERITAGE ELEMENTS FROM THERMOGRAPHIC IMAGES

I. Garrido[1,] *, S. Lagüela[2], S. Sfarra[3], M. Solla[1,4]

[1] Applied Geotechnologies Research Group, Mining & Energy Engineering School, University of Vigo, Rúa Maxwell s/n, 36310 Vigo (Spain) - (ivgarrido, merchisolla)@uvigo.es
[2] TIDOP Research Group, EPS Ávila, University of Salamanca, Calle Hornos Caleros 50, 05003 Ávila (Spain) - sulaguela@usal.es
[3] Department of Industrial and Information Engineering and Economics (DIIIE), University of L'Aquila, Piazzale E. Pontieri 1, I-67100 Monteluco di Roio, L'Aquila (Italy) - stefano.sfarra@univaq.it
[4] Defense University Center, Spanish Naval Academy, Plaza de España s/n, 36920 Marín (Spain) – merchisolla@cud.uvigo.es

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**ABSTRACT:**

Heritage elements, from historic buildings to stone sculptures and panels, stand as key elements in the history of humanity. Unfortunately, the deterioration of both the surface and the interior of these elements is inevitable, endangering the quality and existence of these structures of high historical value in the event of a delay in the implementation of the required maintenance tasks. InfraRed Thermography, IRT, appears as one of the most recent techniques to detect and characterize possible pathologies in structures in their early stages, being very useful for a preventive analysis in heritage elements.

This paper presents a methodology for the automatic detection and characterization of one of the most severe and frequent pathologies in heritage structures, moisture, from thermal images. The proposal stands as a demonstration of the potential of the IRT technique for heritage conservation applications, and as a new step towards the automation of the inspection process and optimization of the decision-taking in conservation actions within cultural heritage. For that, two thermal criteria and a semi-automatic image rectification process are implemented as main phases of the methodology, obtaining good results for the detection of moisture zones and accurate area values with regard to the real dimensions of each moisture zone. Specifically, an F-score average of 78%±19% regarding detection performance and a percentage relative error of minimum 4%, and maximum of 12%, referred to the area computation in unit metrics are obtained.

## 1. INTRODUCTION

According to Cadelano et al. (2015), the conservation of heritage elements requires the knowledge of the phenomena involved in the processes of deterioration of the affected areas. These include: i) biological/mould growth, ii) efflorescence/salt crystallization, and iii) cracking and detachment as decay mechanisms. All of them can be caused by moisture through the following corresponding actions:

i) water promotes the development and expansion of the mould in non-nutritive materials with traces of organic matter contamination.

ii) water precipitates and crystallizes certain water-soluble salts, when water is evaporated in a material.

iii) water changes its volume through its change of state, liquid-solid-vapour, generating pressure or depression inside the pores of materials.

Consequently, the detection and characterization of moisture at an early stage in heritage elements are essential to avoid irreversible damage in their surfaces and interiors. With this

purpose, Non-Destructive Testing (NDT) techniques are defined as ideal tools for performing the above tasks, since they do not damage the heritage elements under study (Riveiro, Solla, 2016). InfraRed Thermography (IRT) stands among the most appropriate NDT methods for moisture analysis because of the following advantages: i) remote and real time operation, ii) high accuracy and high-speed scanning, iii) non-emission of harmful radiations and iv) easily interpretable results in 2D (Garrido et al., 2018a).

IRT consists of a technique that measures the temperature of the surface of a material by means of thermal sensors (Garrido et al., 2018a), saving the measurements in image format. The thermal sensors are typically incorporated in a camera, known as Thermal InfraRed (TIR) or thermographic camera.

For the specific case of moisture, the presence of water generates an anomalous temperature distribution that is reflected on the superficial temperature of the material prior the water reaches the surface. This thermal print is different with regard to the temperature distribution of the unaltered environment (Bagavathiappan et al., 2013), and can consequently be detected using IRT.

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* Corresponding author

As will be seen in Section 2, there are several investigations focusing on the application of IRT to moisture analysis. However, all these IRT studies require the interpretation of the data by a human operator, increasing the risk of a wrong assessment due to the high-level of subjectivity and dependence on the expertise of the operator, except for Garrido et al. (2018b) and Garrido et al. (2019). Then, with the aim of taking a step forward towards the automation of the inspection process and optimization of the decision-taking in conservation actions within cultural heritage, this work presents a methodology for the automatic detection and characterization of moisture in heritage elements, from the thermal images acquired with IRT. For that, this paper is structured as follows: first, Section 2 describes an overview of the most recent IRT works on the analysis of moisture. Secondly, Section 3 explains the main steps of the methodology developed, showing the results and discussion of its application in various tests in Section 4. Finally, Section 5 contains the conclusions reached.

## 2. RELATED WORK

Analysing the most recent IRT works related to the study of moisture, two different approaches can be contemplated both during the acquisition and the post-acquisition phases. Some IRT research perform the acquisition by applying some natural thermal excitation source, such as solar radiation, with the aim at measuring the surface temperature differences between moisture and unaltered environment. With this approach, called passive IRT, it is only possible to detect and characterize moisture that thermally affects the material surface, compensating this limitation through its simpler and faster experimental setup. Otherwise, the use of artificial thermal excitation, such as lamps and heaters, allows a better thermal contrast of the acquired thermal images, in addition to detect and characterize internal moisture (active IRT).

Regarding passive IRT, it is possible to identify changes in moisture content on adhered ceramic façades by analysing their different thermal behaviour at different hours (Edis et al., 2015) or days (Edis et al., 2014). As both works detect changes in moisture content during the post-acquisition stage, this approach is known as qualitative IRT, in which the only purpose is to detect anomalous areas. Instead, if the objective is to determine some characteristics of the moisture, the approach is denominated as quantitative IRT.

More examples of passive IRT are: i) Garrido et al. (2018b) and Garrido et al. (2019), which search moisture areas on surfaces of internal/external walls and of construction materials of different scale sizes, respectively (qualitative IRT), ii) Barreira et al. (2016), who assess moisture related phenomena in building components (qualitative IRT), iii) Georgescu et al. (2017), who monitor the interior of a church to evaluate improvements made after restoration works in search of moisture areas to remove (qualitative IRT), and iv) Barreira et al. (2017), who analyse the humidification phenomena in lightweight concrete specimens, both in qualitative and quantitative IRT.

Moreover, with active IRT, i) Cadelano et al. (2015) evaluate the decomposition of fresco mural painting inside of a medieval chapel through the detection of the presence of water on the decorated surfaces and inside the walls, considering

solar radiation as an "artificial" thermal source (qualitative IRT), while ii) Sfarra et al. (2016) use two halogen lamps to analyse the state of a mural painting in combination with other NDT and micro-destructive analytical techniques, identifying a sandwich structure having the interstitial void full of moisture (qualitative IRT), among others, and iii) Sfarra et al. (2017) evaluate the state of conservation of a mosaic testing it through different experimental setups, among them by applying a halogen lamp where the interior water made as artificial defect is detected (qualitative IRT).

## 3. METHODOLOGY

The method proposed consists of three main phases applied to a single thermal image at a time, being the images acquired in passive IRT. Figure 1 shows the workflow of the methodology, using one of the case studies analysed in Section 4 as example of input thermal image (Test_1).
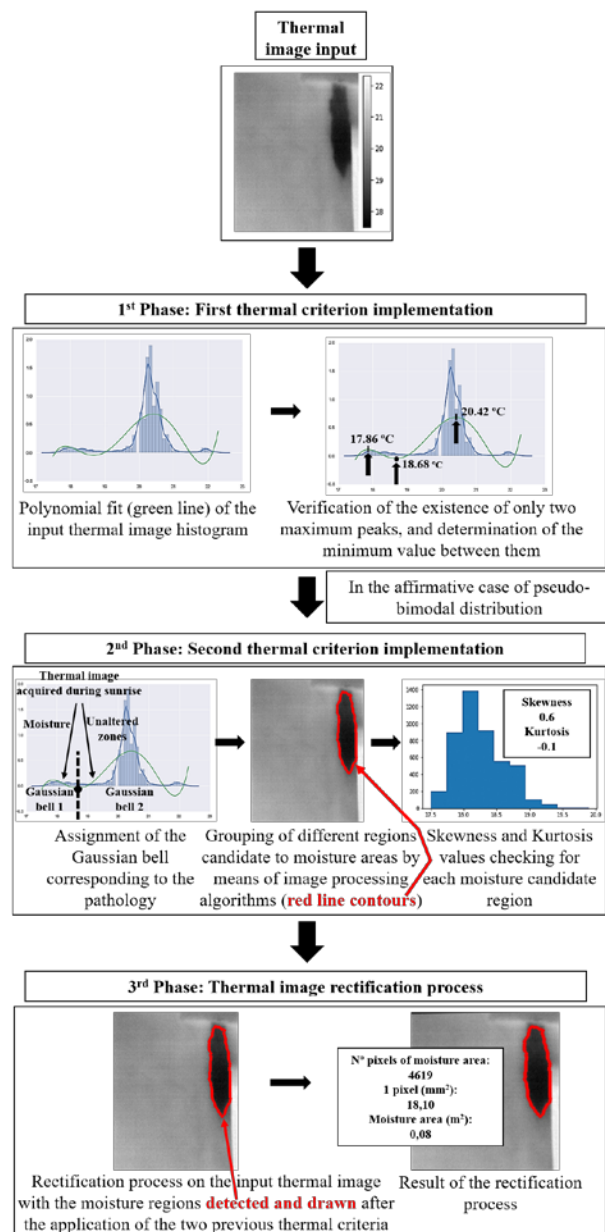


Figure 1. Workflow of the methodology

In the first phase, the histogram of the input thermal image is adjusted to a polynomial equation in order to automatically obtain the minimum value between the two maximum peaks of the histogram. This is based on the thermal criterion that the temperature distribution of a thermal image of a structure, with areas affected by pathologies, presents an approximate bimodal distribution. In other words, the thermal image histogram of a heritage element with moisture areas consists roughly of a combination of two Gaussian distributions, one belonging to the unaltered zones and the other to the pathology (Garrido et al., 2019). Thus, by counting the number of maximum peaks in the histogram of the thermal image, it can automatically be determined whether (2 maximums peaks) or not (more or less than 2 maximums peaks) a material will have anomalous areas.

In the case of pseudo-bimodal distribution (2 maximums peaks in the thermal image histogram), the minimum value between the maximums peaks is considered as the point of overlap between the Gaussian distributions of the unaltered areas and the moisture, respectively. With the purpose of knowing which Gaussian bell of the pseudo-bimodal distribution belongs to moisture, the following hypotheses are considered on the second phase of this method:

1) Thermal image acquired during sunrise: the Gaussian bell of moisture is located at the left regarding the point of overlap, because the evaporative cooling and the increased heat storage capacity in the moisture area slow the temperature increase with respect to the temperature increase of the unaltered environment.

2) Thermal image acquired during sunset: the Gaussian bell of moisture is located at the right regarding the point of overlap, because the condensation process and the increased heat storage capacity in the moisture area slow the temperature decrease with respect to the temperature decrease of the unaltered environment.

In this way, the temperature range of moisture can be known automatically, by directly grouping different candidate regions to moisture areas with the help of the application of some image processing algorithms. The first one consists in the application of the morphological dilation process (Balado et al., 2019) on the thermal image by means of the previous creation of a binary mask, allowing to group nearby pixels that are not colliding but that have their values within the moisture temperature range. Next, a method of connecting components (Riveiro et al., 2018) is used, labelling each candidate region to moisture area in order to separate among them. With the last purpose, and as last step of this second phase, it is possible to calculate separately the Kurtosis and Skewness values regarding the temperature distribution of each candidate region, allowing the automatic verification of the Gaussian distribution. Then, with these parameters, the effect of noise (non-Gaussian distribution) appearing as false Gaussian bell is discarded.

Regarding the last phase of the methodology, and after automatically detecting the possible regions affected by moisture on the heritage element under study, two different steps are applied in order to geometrically characterize each moisture area detected and drawn on the input thermal image. The first step is a semi-automatic image rectification applied to

the input thermal image. By means of the image rectification process, the area of a pixel in metric magnitudes can be obtained. This process is semi-automatic as four control points on the input thermal image must be manually assigned beforehand, knowing their real relative distances. The second step, automatic, consists of counting the number of pixels in each moisture area from the rectified thermal image. Consequently, the real surface value of each moisture zone is known.

## 4. RESULTS AND DISCUSSION

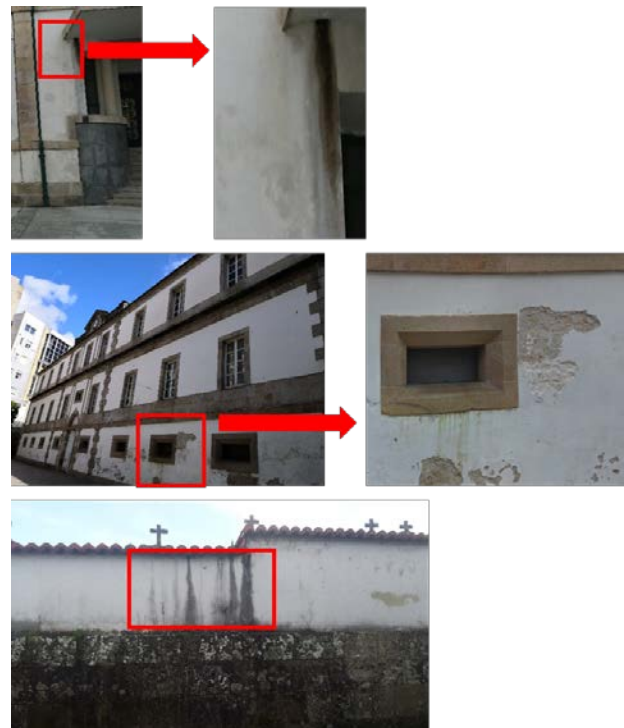This methodology has been tested in several heritage elements, showing their visible images in Figure 2.



Figure 2. Visible images of the case studies (regions of interest in red rectangles). Reference name, from top to bottom: Test_1, Test_2 and Test_3

As can be observed, Test_1 consists of a part of a wall belonging to an academic building built during the first half of the last century. Test_2 tests a wall belongs to a museum building built in the mid-19th century. Last, Test_3 is a part of the wall of an 18th century cemetery. The corresponding input thermal images are represented in Figure 3, reflecting on the right side of each image their corresponding temperature scales (in ℃). It can be seen that there are signs of moisture in all images. The acquisitions were made: Test_1 during the sunrise, and Test_2 and Test_3 during the sunset.
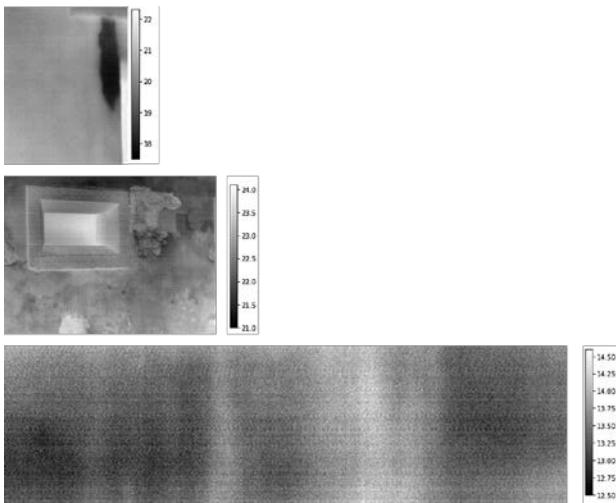
Figure 3. Input thermal images of the analysed case studies.
From top to bottom: Test_1, Test_2 and Test_3

Figure 4 graphically shows the results of the moisture regions detection obtained with this methodology, representing on the right side of each result the corresponding real regions verified by an expert operator.
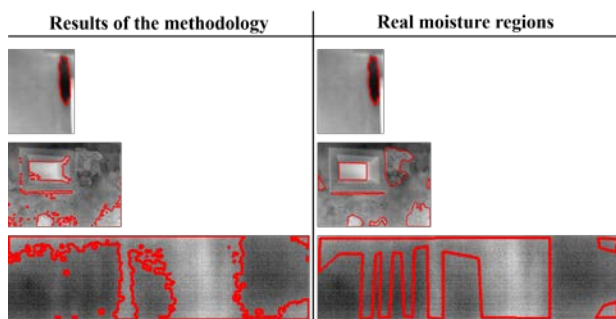


Figure 4. Results of the methodology in each case study (red lines), representing on the right side of each result the corresponding real moisture regions (red lines). From top to bottom: Test_1, Test_2 and Test_3

To quantify the qualitative results, the following performance metrics (values in percentage) are defined:

$$Precision = \frac{TP}{TP + FP} \qquad (1)$$

$$Recall = \frac{TP}{TP + FN} \qquad (2)$$

$$F - score = 2 * \frac{Precision * Recall}{Precision + Recall} \qquad (3)$$

where TP, FP and FN are the number of true positives/pixels, false positives/pixels and false negatives/pixels, respectively and regarding between the detected and the real moisture areas. Results of precision, recall and F-score performance metrics for each case study, and the global average and standard deviation, are shown in Table 1.

|  | Precision (%) | Recall (%) | F-score (%) |
|---|---|---|---|
| Test_1 | 96 | 99 | 98 |
| Test_2 | 66 | 54 | 60 |
| Test_3 | 83 | 73 | 78 |
| Average (%) | 82 | 75 | 78 |
| Standard deviation (%) | 15 | 22 | 19 |

Table 1. Precision, recall and F-score results for each case study in addition to the global average and standard deviation

Analysing the previous results, the methodology developed gives good results for detection of moisture areas, with values generally higher than 70%. In Test_2 the results are the poorest due to solar reflection at the time of thermal image capture, decreasing the performance of the IRT. So, it is very important that the acquisition of thermal images is done during the sunrise/sunset just before/just after the appearance/disappearance of sunlight, respectively, trying to make the captures as perpendicular as possible.

Referring to the calculation of the area in metric units in each of the regions of moisture detected in Figure 4, Table 2 shows the values obtained and the estimation error of this quantitative analysis comparing with the real values through the absolute error and percentage relative error calculations.

|  | Test_1 | Test_2 | Test_3 |
|---|---|---|---|
| Moisture area calculated (m$^2$) | 0,084 | 0,839 | 1,729 |
| Absolute error (m$^2$) | 0,003 | 0,057 | -0,244 |
| Percentage relative error (%) | 4% | 7% | -12% |

Table 2. Area value obtained for each detected moisture region in metric units, in addition to their corresponding absolute error and percentage relative error values

As can be seen, the methodology proposed also offers an acceptable geometric characterization, although accuracy is dependent on the area: the higher the area, the lower the accuracy of the area estimation. In addition, given the good performance regarding the geometric characterization, the results of Table 1 can be shown as detected/undetected moisture area, and area falsely detected as moisture, for each of the case studies in metric units (Table 3).

|  | Test_1 | Test_2 | Test_3 |
|---|---|---|---|
| Detected moisture area (m$^2$) | 0,084 | 0,839 | 1,729 |
| Undetected moisture area (m$^2$) | 0,001 | 0,383 | 0,473 |
| Area falsely detected as moisture (m$^2$) | 0,003 | 0,286 | 0,292 |

Table 3. Detected/undetected moisture area, and area falsely detected as moisture, for each of the case studies in metric units

## 5. CONCLUSIONS

This work shows a methodology for the automatic detection and geometric characterization of moisture areas in heritage structures from thermal images. Through the application of 3

main phases in different case studies, the first two phases based on thermal criteria that analyse the temperature distribution regarding the images, for the detection process, and the third phase focusing on the image rectification process, for the geometric characterization process, acceptable results have been obtained. Referring to the detection performance, average values of 82%±15%, 75%±22% and 78%±19% for precision, recall and F-score are obtained, respectively. Regarding the geometric characterization, the real area of each region of moisture is obtained, with minimum values of 0,003 $m^2$ and 4%, and maximum values of -0,244 $m^2$ and -12%, with respect to absolute error and percentage relative error parameters, respectively.

Future researches will deal with the automatic detection of Gaussian bells with moisture in a more robust way than the polynomial adjustment process of the thermal image histogram under study, and automatically classify several types of pathologies in a same thermal image, such as moisture and cracks, following the line of (Garrido et al., 2018b).

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