Automated Thermal Fault Detection in Ultra-High Voltage Substation Equipment ⋆

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Abstract: Inspection of ultra-high voltage substations (UHVS) plays a crucial role for ensuring the stability of power grids and preventing damage that can potentially lead to serious power loss. Automating the inspection process provides early detection of equipment faults, improved safety and cost efficiency. This paper presents an automated visual inspection system, using an RGB and thermal camera mounted on an autonomous ground robot. Our approach leverages component detection in RGB images with YOLOv11n, followed by multi-modal image matching to locate components in thermal imagery and a rule-based anomaly detection algorithm. Experimental results in an operational power substation demonstrate the system's ability to detect early-stage thermal anomalies, highlighting its potential for improving substation reliability and operational safety.

Keywords: thermal inspection, autonomous robot, RGB - thermal image matching, ultra-high voltage substation

1. INTRODUCTION

The reliable operation of ultra-high voltage substations (UHVS) is critical for the stability of electrical transmission networks, necessitating advanced inspection methods to monitor equipment integrity. To this end, condition-based instead of time-based inspection can significantly minimize equipment faults. However, condition-based monitoring requires cost-effective technology that enables systematic inspection of equipment and automatic processing of the acquired data to achieve early fault diagnosis.

Automated robotic inspection offers an effective solution by enabling continuous, precise assessments of essential components while minimizing risks associated with human intervention in high-voltage environments. Utilizing high-resolution RGB and thermal imaging, these systems can detect early signs of insulation degradation, overheating, or structural wear in transformers, circuit breakers and other critical equipment. By identifying potential failures before they escalate, automated inspection enhances system reliability, improves safety, optimizes maintenance scheduling, and reduces long-term operational costs.

This paper introduces an automated visual inspection system, equipped with an RGB and thermal camera on an autonomous ground robot. Our work is part of the ENORASI project (`www.enorasi-insight.com`) regarding the automation of the inspection process in Ultra-High Voltage Substations using autonomous ground vehicles. The robot is given a list of selected electrical components for inspection, based on factors such as past thermal or optical wear, time interval since the last inspection and the criticality of each component. Our system creates an optimal visitation plan for the components using a 3D map of the UHVS, identifies key visibility points for each component and deploys the robot to the field in order to capture RGB and thermal images. The entire inspection process is streamlined, supporting an inspection schedule with minimal human involvement.

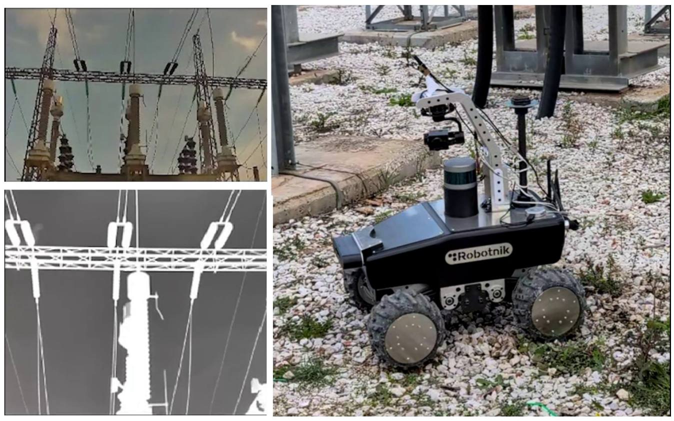

Fig. 1. View of the inspection robot in the field. RGB and Thermal images, as seen from the camera, are also presented on the left.

Our robotic system is the Summit-XL mobile robot (Robotnik Automation S.L.) equipped with the ViewPro Z10TIR thermal camera, mounted on an appropriate motorized gimbal platform (Fig. 1). Various other sensors are also utilized, such as LIDAR, IMU and wheel encoders, that are used for navigation, perception of the environ-

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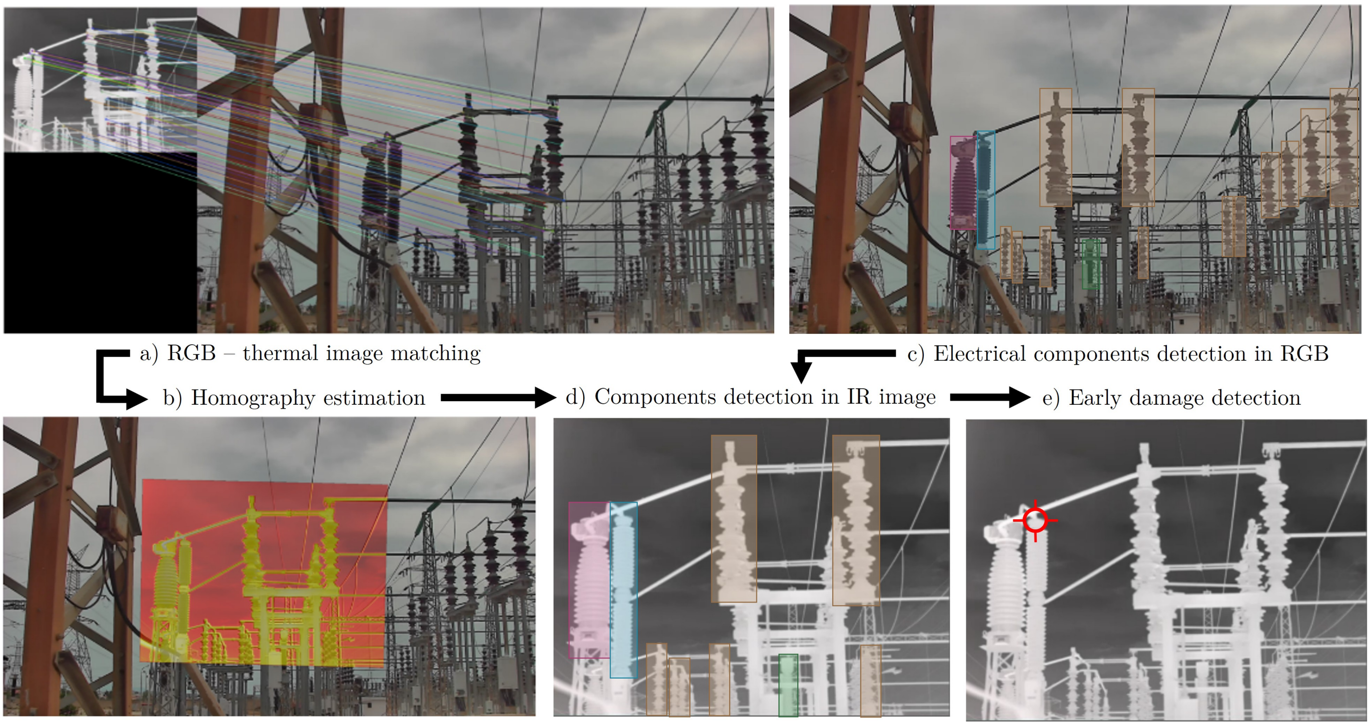


Fig. 2. Overview of the proposed thermal inspection pipeline.

ment, localization on the map etc. In the following, we present an overview of our thermal inspection algorithm, analyzing the various components, along with experimental results from actual images collected from an UHVS in Greece.

2. RELATED WORK

Modern electrical equipment detection leverages both visible-light and infrared imaging techniques to identify and assess components in power systems. Traditional approaches (Wu and An, 2014; Reddy et al., 2013), mainly rely on texture analysis to detect insulators and estimate their condition. On the other hand, Deep Learning architectures, especially Convolutional Neural Networks (CNNs) (Khan et al., 2020) have been shown to be extremely effective in many tasks, including detection and evaluation of electrical equipment. Therefore, most recent works build upon well-known deep learning models, especially object detectors, to identify electrical components in RGB or infrared images. Gong et al. (2018) modify the YOLO object detector by introducing an additional term in the loss function to enforce orientation consistency among the estimated bounding boxes. Liu et al. (2020) also use YOLO to detect four types of insulators in RGB images. Miao et al. (2019) proposed an insulator detection method based on the SSD object detector, customized for aerial imagery through a two-stage fine-tuning scheme. Similarly, Qi et al. (2023) modify the SSD object detector using compression strategies employed in squeezenet, to detect 5 electrical substation instruments. Wang et al. (2020) use Mask-RCNN for instance segmentation of insulators in infrared images, and use a rule-based approach for fault detection based on past temperature data. Zheng et al. (2021) design a multi-scale version of the FSSD detector for insulator detection in thermal images, by fusing feature maps at different levels of the network.

Automatic hot-spot detection on electrical equipment from thermal images has also received significant attention. Due to the lack of large annotated datasets, many works rely on traditional approaches like K-means clustering (Salazar and Macabebe, 2016; Mohd et al., 2017), or thresholding methods (Alajmi et al., 2019), such as Otsu's method (Afifah et al., 2021). In Ali et al. (2022) the authors use handcrafted descriptors, such as HOG, LBP, RGB, contrast, correlation and energy descriptors as well as SURF coupled with classifiers, such as SVMs and k-NN to classify thermal images of photovoltaic cells into 3 health conditions. Song et al. (2023) use SURF features, Bag-of-Words and SVMs to classify circuit board images as normal or having faults that manifest as hot-spots.

Recently, deep learning approaches have also been proposed to address this problem. Ahmed et al. (2023) use pre-trained models like ResNet18, SqueezeNet, and GoogleNet for feature extraction coupled with traditional classifiers, such as SVMs and k-NN. In addition, many widely used object detection architectures like VGG16 (Ukiwe et al., 2024) and YOLO (Sun et al., 2022; Hamid et al., 2024; Pérez-Aguilar et al., 2024) have been repurposed to detect hot-spots in thermal images. Goyal and Rajapakse (2024) introduce 2-step approach for hot-spot detection: a) they classify thermal images as "anomalous" and "normal" using a self-supervised approach involving a modified SimSiam framework with an XceptionNet backbone and a modified loss to include a cross-entropy function, and b) they use GradCam (Selvaraju et al., 2017) to generate heatmaps showing the contribution of each image area to the classifier's output.

3. METHODOLOGY

Early damage of electrical components usually manifests as irregular heat distribution across the instruments, the conductors or their connection, implying that inspection should be carried out mainly using thermal imagery. However, components' detection in thermal images is not favorable due to the lack of large annotated thermal datasets and efficient methods. Therefore, we propose to detect electrical components using the RGB channel, and identify potential damage on the thermal image, after matching the two. Figure 2 shows an overview of our proposed pipeline.

3.1 Electrical instrument detection

Object detection is extensively studied in the computer vision literature, often serving as reference to benchmark new methods. Deep neural networks, especially Convolutional Neural Networks (Khan et al., 2020) and lately Transformers (Shehzadi et al., 2023) have revolutionized the field. This progress has also been driven by the existence of large image datasets, such as the well-known ImageNet (Deng et al., 2009) for image classification, the COCO dataset (Lin et al., 2014) for object detection and segmentation and others (Everingham et al., 2010; Geiger et al., 2013). However, these large multi-category datasets usually concern general classes that are not suitable for robotic applications. Specifically, many robotic applications, such as automatic inspection, require the detection of a small set of specialized objects in cluttered and heavily occluded scenes (De Gregorio et al., 2020). To mitigate the lack of large amounts of data for specialized applications, transfer learning approaches are usually employed, by using pre-trained models on large datasets and fine-tuning them on a smaller specialized set that fits the problem.

There are two main deep learning approaches for object detection: (a) Two-stage methods (Girshick et al., 2014; He et al., 2017), which first estimate candidate regions containing objects and subsequently classify the corresponding image patches, requiring two separate networks; and (b) Single-stage methods (Redmon et al., 2016; Liu et al., 2016) which use a single network for detection and classification and are therefore more computationally efficient.

To detect electrical instruments, we use YOLOv11n (Redmon et al., 2016), a single-stage object detection method that offers high performance with relatively low computational requirements, which makes it suitable for deployment on mobile robots. We employ a pre-trained model and fine-tune it using manually annotated data acquired from an actual power substation. Specifically, we have collected 30 minutes of video in which 6 different classes of electrical components appear (Figure 3). After downsampling the video, we have manually annotated 1468 frames containing 7923 components in total. We also use random crops, scaling and flipping for data augmentation. Electrical components are mainly distinguished by their upper part (cap) and its connections, while the lower part (insulator) is present in all components and in most cases its appearance is not indicative of the component class. In addition, most elements are positioned more than 3.5 m

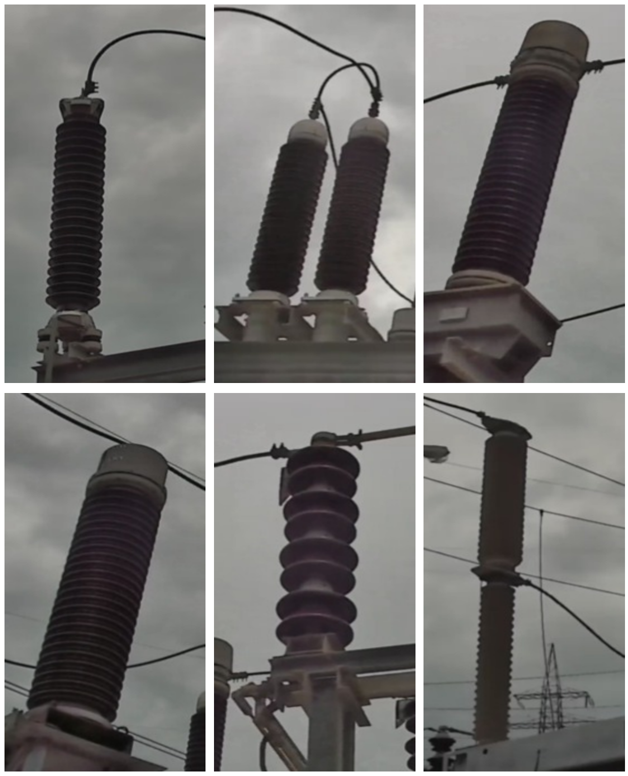


Fig. 3. Recognized electrical components. From left to right and from top to bottom: surge arrester, bushings, current transformer, voltage transformer, isolator, circuit breaker.

above ground. As a result, depending on the robot/camera configuration, only the insulator may be visible. In such cases, recognizing when only the insulator is in view can help the robot and camera control system accurately aim at the electrical component. To address this, we classify the insulator as a separate category.

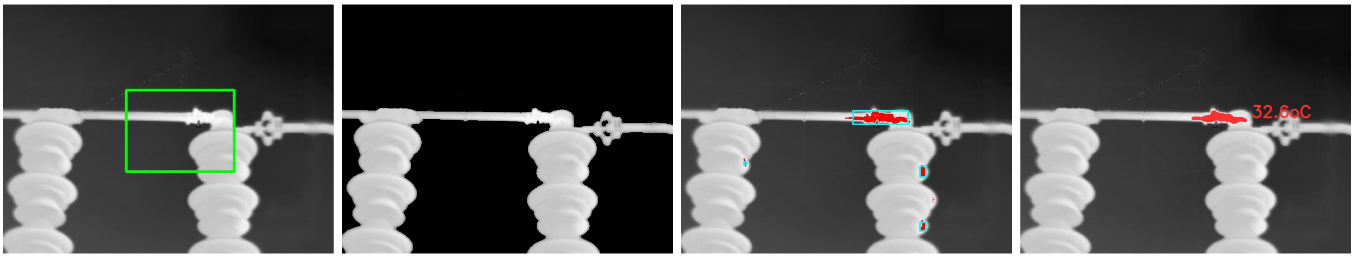
3.2 RGB-thermal image matching

To identify early signs of wear, electrical instruments must be detected in the thermal channel. Following detection on the RGB image, the estimated bounding boxes are projected on the thermal image, by estimating the homography $\mathbf{H}$ that transforms RGB image coordinates $\mathbf{x}_{RGB}$ to thermal image coordinates $\mathbf{x}_{th}$:

$$\mathbf{x}_{th} \sim \mathbf{H}\mathbf{x}_{RGB}.$$

A common way to estimate $\mathbf{H}$ is to extract features from both images that encode interest points, edges, object contours or other salient structures and look for matches among them. Representing images with these features makes these methods robust to changes in luminosity, viewpoint and other transforms.

However, most methods focus on matching color images only, while few deal with multi-modal matching, i.e., matching images acquired from different types of optical sensors. The latter is particularly challenging, due to the nonlinear radiometric differences between the two sensors and the resulting luminance values that are recorded (Jiang et al., 2021), which add up to other sources of nonlinear changes (optical distortions, changes in illumination). For this reason, many traditional gradient-based



(a) (b) (c) (d)

Fig. 4. Thermal fault detection. (a): original image with ground truth from human operator, (b): background subtraction, (c) high temperature regions (d) estimated hot-spots with mean temperature.

features, such as SIFT are often insufficient for multi-modal matching.

Radiation-variation Insensitive Feature Transform (RIFT) (Li et al., 2020, 2023) is a feature extraction method specifically designed for multi-modal matching. RIFT uses the phase congruency to detect keypoints that correspond to edges and corners. These features are described by constructing a maximum index map, which encodes orientation. To estimate the homography between the RGB and thermal images, we extract RIFT features from both images and find keypoint pairs with the minimum absolute difference. $\mathbf{H}$ is estimated by the Direct Linear Transformation algorithm along with RANSAC to reject outliers.

3.3 Thermal fault assessment

Early deterioration of electrical components typically shows as areas of abnormal heat distribution, signaling more serious defects that may lead to system failure and subsequent power supply interruptions. In contrast to their significant consequences, such faults occur infrequently, and thermal images documenting these defects remain scarce. This scarcity of data limits the application of machine learning methods, which typically require substantial datasets, even when implementing transfer-learning approaches.

Local guidelines regarding thermal inspection of power substations dictate that potential instrument fault is indicated by temperature values 10°C greater than the ambient temperature. To detect faults in thermal images we follow a simple yet effective rule-based approach that complies with these guidelines (Figure 4):

- The background is removed using Otsu's thresholding method (Otsu, 1979).
- A reference temperature is computed as the median temperature of all foreground objects. This serves as a rough estimate of the ambient temperature.
- The image is denoised with median filtering and the pixels with the top 90% temperature values are isolated.
- Potential hot-spots are detected in the resulting binary image by connected components analysis with 8-way connectivity (Bolelli et al., 2020).
- Connected components whose mean temperature differs more than 10°C from the reference temperature are considered potential hot-spots.

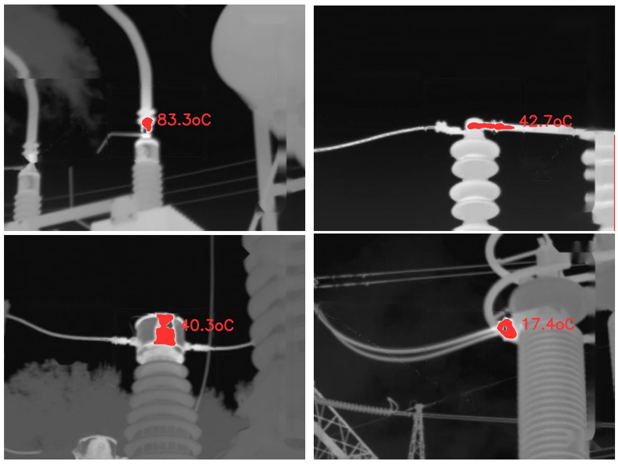


Fig. 5. Examples of fault detection in thermal images, showing each hot-spot's mean temperature. To be classified as fault area, a candidate hot-spot's temperature must be at least 10°C higher than the estimated environmental temperature.

4. RESULTS

To assess the performance of electrical component detection, we randomly split our RGB dataset and use 80% to fine-tune YOLOv11n and 20% for validation. Detection is considered correct if the Intersection Over Union (IoU) between the estimated bounding box and the ground truth is $> 50\%$. Results are reported in terms of F1 score and mean Average Precision (mAP), given by:

$$\mathrm{mAP} = \frac{1}{C}\sum_{1}^{C} \mathrm{AP_c}, \tag{1}$$

where $C = 7$ is the number of component classes and $\mathrm{AP_c}$ is the area under the precision-recall curve for class c and for different values of the confidence threshold. The network achieves 96.7% mAP and 94% F1 score across all 7 classes, showing the effectiveness of our proposed method and the power of the transfer learning approach. Per class results (Table 1) also demonstrate that the performance is relatively uniform across all instrument types. The main source of the small error is apparent after inspecting the confusion matrix (Figure 6): some instances are misclassified as background, which may be due to imperfections in the annotations and the relatively low amount of data used for fine-tuning. Another source of error are elements in close proximity to each other and in a large distance from the robot, which the detection algorithm falsely groups

Predicted \ True	BS	SA	VT	CT	IS	CB	INS	BG
BS	0.99	0	0	0	0	0	0	0.03
SA	0	1	0	0	0	0	0	0.02
VT	0	0	0.97	0.01	0	0	0.04	0.04
CT	0	0	0.01	0.97	0	0	0	0.09
IS	0	0	0	0	0.95	0	0	0.63
CB	0	0	0	0	0	0.93	0	0.08
INS	0	0	0.01	0.01	0	0	0.94	0.12
BG	0.01	0	0.01	0.01	0.05	0.07	0.02	0

Fig. 6. Confusion matrix for electrical component detection. SA: surge arrester, BS: bushings, CT: current transformer, VT: voltage transformer, IS: isolator, CB: circuit breaker, INS: insulator, BG: background

into a single element. The aforementioned types of error are also related to the non-maximum suppression that YOLO performs.

To assess the accuracy of our estimated homography, we calculate the mean reprojection error for the N matches computed by RIFT2:

$$E = \frac{1}{N} \sum_{i=1}^{N} \left\| \mathbf{x}_{th}^{i} - \mathbf{H}\mathbf{x}_{RGB}^{i} \right\| .$$

Our approach results in a mean reprojection error of 2.46 pixels, demonstrating its effectiveness for RGB-thermal image matching.

For fault assessment, we compiled 84 reports from a human professional operator who performed periodic inspections of the power substation and annotated hot-spots in a 2-year period using a handheld camera. The resulting dataset contains 84 RGB-thermal image pairs. Our algorithm correctly detects thermal faults in 76/84 cases, indicating that efficient methods that run in real-time can be successful in detecting hot-spots. Most errors result from erroneous mapping of image intensity values to temperature values in the report compilation process. Figure 5 shows indicative results of our fault detection algorithm. The electrical components of the UHVS are arranged in a grid-like configuration, which enables the acquisition of RGB and thermal images of each component from different viewpoints. To increase our system's robustness, at inspection time we capture images from 4 different directions. As a result, if a fault is undetected in a certain view, it can be effectively identified and compensated for through detection in another view. This redundancy enhances the accuracy and reliability of the fault detection process. The whole system requires approximately 200ms to process a single RGB-thermal image pair using the robot's CPU only.

Table 1. Precision (P) and Recall (R) for detecting each instrument class.

	BS	SA	VT	CT	IS	CB	INS
P	0.973	0.992	0.975	0.971	0.902	0.938	0.845
R	0.975	1	0.968	0.965	0.844	0.895	0.932

5. CONCLUSION

This paper presented an automated thermal inspection system for Ultra-High Voltage Substations using an autonomous ground robot equipped with RGB and thermal cameras. Our approach demonstrates the effectiveness of utilizing the RGB channel for electrical component detection combined with thermal imaging for fault assessment, despite the lack of specialized datasets. The system's ability to operate autonomously with minimal human intervention represents a significant advancement in UHVS inspection, potentially reducing maintenance costs, improving safety by eliminating human exposure to high-voltage environments, and enhancing reliability through early fault detection. Future work will focus on expanding the thermal fault dataset, enabling the development of more sophisticated anomaly detection algorithms and on unifying the detection and fault assessment processes. These improvements would further enhance the robustness and applicability of the proposed system in real-world substations.

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