Infrared thermography-based diagnostics on power equipment: State-of-the-art

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Abstract
As a non-contact temperature distribution measurement method, infrared thermography (IRT) has emerged as an indispensable tool in condition monitoring and fault diagnosis of electrical equipment based on the absolute and relative temperature values. Manual fault inspection, as an expert-experiences based evaluation method, has formed a mature technical scheme with a large number of application cases. However, the efficiency and accuracy of manual fault inspection are being challenged by the rapid growth in the number of equipment in power grid. The situation is improving with the advanced of image processing technique. Machine-assisted fault diagnosis provides a novel method to assist human beings to complete fault diagnosis under the intervention of human prior knowledge. However, the limitations of infrared images bring challenges to image analysis processing especially target detection. In pursuit of automatic fault diagnosis, deep learning algorithms are introduced to achieve target detection in the complex environment. This study reviews the development of IRT-based diagnostics beginning with the general procedures, objects, and limitations of IRT-based fault inspection, and then gives an insight into the popular machine-assisted fault diagnosis as well as image-based intelligent fault identification. In addition, the future recommendations of IRT are also provided from construction of intelligent infrared detection system, establishment of an open and shared infrared image database and comprehensive utilization of joint visualization diagnosis technology.

1 | INTRODUCTION

A great deal of practical experience shows that in all probability the abnormal working state and insulation degradation of power equipment give rise to heat accumulation which is deemed as a major cause of accelerated ageing even the whole equipment failure [1]. Accordingly, temperature rise monitoring is widely applied to early manifestation of insulation failure, overloading as well as inefficient operation for transmission and transformation equipment in the power system. Infrared thermography (IRT), as a high sensitive, precise and non-contact temperature distribution measurement [2], has become one of the most indispensable condition monitoring and fault diagnosis tools of electrical equipment in past decades [3], and has significantly enabled and improved on/off-line monitoring and routing inspection in substation and transmission line.

The development of IRT-based fault diagnostics on power equipment, in retrospect, could be summed up with three stages, namely manual fault inspection, machine-assisted (or semi-automatic) fault diagnosis and image-based intelligent fault identification. Manual IRT fault inspection is a manual-based IRT, which relies on the years of summary of long-term fault field experience and human prior knowledge which can hardly be equally shared by others. In the past half century, the manual fault inspection formed a mature technical scheme with a large number of application cases [4, 5]. In such inspection, well-qualified and experienced workers are of the essence throughout the entire process including visual object identification, thermal image acquisition, overheating region searching and fault matching with judging index. Admittedly, such manual fault diagnosis method is flexible in field application, but it is over-reliant on subjective and indescribable experience.
and time-consuming especially for a whole substation. The efficiency and accuracy of the manual IRT fault diagnosis are increasingly being challenged by the rapid growth in the number of equipment in the power grid [6]. As a consequence, some image processing technologies are adopted to replace a part of manual operation and has laid a foundation for a more rapid and accurate machine-assisted fault diagnosis [7]. Machine-assisted fault diagnosis, also known as semi-automatic fault diagnosis, is a method that uses computers to replace human beings to complete primary target detection, temperature information extraction and assist human beings to complete fault diagnosis under the intervention of human prior knowledge. In general, the fault diagnosis is implemented in two steps, that is, extracting the object regions from the background with image segmentation and feature extraction algorithms, and evaluate the overheating fault with judgement criteria [8]. The bottleneck in this stage is the extraction of equipment regions and the recognition of multiple types of equipment under complex background [3]. With deep learning (DL) algorithms, represented by convolutional neural network (CNN), image processing has been promoted to a new stage in the field of object detection [9]. We name this stage as image-based intelligent fault identification, and in this stage the artificial intelligence algorithms have been introduced to achieve target detection in complex environment. Compared with the machine-assisted fault diagnosis method, the self-learning ability and generalization ability of artificial intelligence algorithms can realize the simultaneous recognition of multiple types of devices by using the trained model without human intervention. That is, it places greater emphasis on detecting a broad range of equipment types, even different instances of the same object class, instead of specific object category. Some intelligent image processing models have been introduced and tailored for IRT-based fault identification and demonstrated excellent results in terms of efficiency and accuracy [10].

In this study, the status and development of IRT-based diagnostics on power equipment are collated and summarized in terms of hardware capability, fault identification procedure, traditional and state-of-the-art thermal image processing approaches, clarifying the future development. The study is organized as follows: In Section 2, the fundamentals and the limitations of the IRT are briefly introduced. The typical thermal faults of power equipment and the general diagnosis procedure in field are demonstrated in Section 3. In Section 4, some traditional image processing approaches are collated. In Section 5, intelligent processing methods tailored for IRT-based fault diagnosis are presented. Finally, some thoughts on existing approaches and prospects for future development are drawn in Section 6. We hope this review provides a reference for innovative IRT-based applications, strategies and algorithm studies.

2 | PRINCIPLES AND LIMITATIONS OF IRT

In order to better apply IRT in fault diagnosis, it is necessary to fully understand its technical principles and limitations.

2.1 | Fundamental principles of IRT

In a nutshell, everything in nature with a temperature above absolute zero (−273°C) radiates infrared at all times, and this infrared radiation carries temperature characteristic information about the object [2]. The generation and propagation of thermal radiation follow the thermal radiation laws:

Planck's law: It shows the relationship between the radiation \( u(T) \) and wavelength \( \lambda \) of radiation emitted from a blackbody, which absorbs all incident radiations and radiates a continuous spectrum, at any temperature \( T \).

\[
u(T) = 3.74 \times 10^8 \lambda^{-5} \left( e^{1.44 \times 10^4 / \lambda T} - 1 \right)^{-1}
\]

where \( u(T) \) is the radiance by the blackbody per unit and per solid angle for a particular wavelength \( \lambda (\mu m) \), \( W \cdot cm^{-2} \cdot \mu m^{-1} \cdot sr^{-1} \). \( T \) is the blackbody temperature, K.

Stefan-Boltzmann law: The total power \( W_b \) radiated by per unit area of a blackbody during per unit time is proportional to the fourth power of the blackbody's temperature \( T \).

\[
W_b = \int_0^\infty u(T)d\lambda = 5.6697 \times 10^{-8} \varepsilon T^4
\]

where \( W_b \) is the total radiant power, \( W/m^2 \). \( \varepsilon \) is the radiation coefficient and the radiation coefficients of common materials of power equipment are shown in Table 1 [11, 12].

Wien displacement law: The wavelength of the peak of the radiation spectrum is corresponding to the blackbody temperature.

\[
\lambda_m T = 2897.7 \mu m K
\]

On this basis, IRT imager collects the thermal radiation emitted by the object and converts it into temperature distribution pictures. This process can be described as the following model which shows the conversion process of thermal radiation signals into electrical signals and pixel values through the optical system, sampling system and detector, as shown as Figure 1 [13].

In Figure 1, \( u_{P_{\omega}}(r_0, \lambda, t) \) is the radiance emitted at point \( P_0 \) of the power equipment in direction \( r_0 \) at time \( t \). \( E_{P_{\omega}}(\lambda, t) \) is the radiance received at point \( P_1 \) (corresponding to \( P_0 \)) in direction \( r_1 \) through the solid angle \( \Omega_{opt} \) subtended by the exit pupil at time \( t \). \( E_{P_{\omega}}(\lambda, t) \) can be calculate by the relation (4).

\[
E_{P_{\omega}}(\lambda, t) = \int_{r_1 \in \Omega_{opt}} u_{P_{\omega}}(r_1, \lambda, t) \cos(\theta) d\Omega_{opt}
\]

where \( \theta \) is the angle of the direction \( r_1 \) to the optical axis. \( u_{P_{\omega}}(\lambda, t) \) is the spectral flux received by the detector area \( A_{det} \) and \( S \) is the electrical signal taken from the detector.
### Table 1: The emissivity coefficient of common materials of power equipment

| Surface Material | Surface State      | Temperature (K) | Emissivity Coefficient $\epsilon$ | Surface Material | Surface State | Temperature (K) | Emissivity Coefficient $\epsilon$ |
|------------------|--------------------|-----------------|-----------------------------------|------------------|----------------|-----------------|-----------------------------------|
| Aluminium        | Highly polished    | 300             | 0.039–0.057                       | Copper           | Oxidation      | 311.15          | 0.87                              |
|                  |                    | 373.15          | 0.09                              |                  |                |                 |                                   |
|                  | Heavily oxidized   | 300             | 0.2–0.31                          | Polished         |                | 311.15          | 0.03                              |
|                  |                    | 366.15          | 0.2                               |                  |                |                 |                                   |
|                  | Anodized           | 300             | 0.77                              |                  |                |                 |                                   |
| Cast Iron        | No oxidation       | 273.15          | 0.21                              | Low-carbon steel | Polished       | 297.15          | 0.10                              |
|                  | Heavily oxidized   | 377.15          | 0.95                              | Ceramics         | Glazing        | 294.15          | 0.45–0.69                         |
|                  |                    | 523.15          |                                   |                  |                |                 |                                   |
| Iron             | No oxidation       | 373.15          | 0.05                              | Marble           | Polished, Gary | 311.15          | 0.75                              |
|                  | Oxidation          | 373.15          | 0.74                              | Ceramics         | Glazing        | 294.15          | 0.45–0.69                         |
|                  | Polished           | 311.15          | 0.28                              | Rubber           |                | 300             | 0.86                              |

### Figure 1: The conversion process of thermal radiation into electrical signal

In the conversion process model, the structures and performance of detectors directly determine the qualities of the infrared images. The development of infrared detectors, in retrospect, could be summed up with four generations [14], as shown in Figure 2. The first generation carried on the infrared (IR) thermal images mainly by the charge coupled device unit or the multi-units scanning the objects. In the advanced second generation, focal plane array detector with numbers of units became the new mainstream direction. The progress of third and fourth generations lies in the development of photosensitive materials: HgCdTe(mercury cadmium telluride), Quantum-well IR photodetectors and type-II superlattice systems. It is expected that the larger number of pixels, higher frame rates, better thermal resolution as well as multicore functionality and other on-chip functions are pursuing goals.
2.2 | Limitations of IRT

The limitations of IRT technology can be summarized as follows [15–17].

- **Low resolution, strong spatial correlation**

  Infrared image technology obtains the object images through the temperature difference between object and environment rather than the boundary or colour information. However, due to the small temperature difference and the low spatial resolution of infrared detectors, infrared images are always with low resolution and strong spatial correlation.

- **Low signal noise ratio**

  Infrared images are always with low signal noise ratio (SNR) because of the complex sources of noise signals during the process of atmospheric propagation, photoelectric conversion, digital signal processing and non-uniformity correction.

- **Heterogeneity** [18]

  The heterogeneity of infrared images will be caused by the response characteristics of detector unit, coupling characteristics of circuit, working state, working environment and other reasons, which will eventually be manifested as noise and distortion of image.

3 | GENERAL DIAGNOSIS APPROACH OF THERMAL FAULTS OF POWER EQUIPMENT

This section collates the general procedures and objects of thermal diagnosis of power equipment. First, the typical faults of power equipment are classified according to the categories of equipment and underlying causes. Then the methods of equipment status evaluation are introduced, and the typical infrared images of multi-type faults of power equipment are given. In the end, the general diagnosis approach is demonstrated with a practical case.

3.1 | Thermal faults of power equipment

Harsh environmental electrifications continue to endure high field, heavy load, contamination, and hazardous stress [19], most of which could give rise to internal or external heat accumulation and accelerate the thermal ageing. Therefore, temperature anomaly is a critical indication to determine the malfunctioning condition of the equipment [7].
According to the categories of equipment and underlying causes, thermal faults can be divided into four categories, that is current-induced heating fault, voltage-induced heating fault, synthetic heating fault and non-electrical fault, as summarized in Table 2 [19]. Current-induced heating faults are common in current-carrying units because of the abnormal increase of electric resistivity or load current [20]. In general, this type of fault is featured by a significant temperature rise. With regard to voltage-induced heating fault, it is normally caused by the increase in dielectric loss, leakage current and local-enhanced field [21]. For synthetic faults, which are caused by electromagnetic effects, such as eddy current and induction current, are normally featured by relatively low temperature [22]. In addition, abnormal temperature change caused by gas leakage is also a common fault [23].

3.2 Abnormal temperature rise judgement

There are three common abnormal temperature rise judgement methods named absolute temperature rise-based method, image feature-based method and homogeneous comparison-based method.

3.2.1 Absolute temperature rise-based judgement

This method is suitable for voltage-induced heating faults and electromagnetic heating faults. The temperature value of the hotspots will be compared with temperature limits for the specific climatic conditions and operating load given in the standards.

3.2.2 Image feature-based judgement

This method is suitable for voltage-induced heating faults. The temperature rise condition is rated by comparing the acquired infrared image to the similar images in normal and abnormal conditions matched in the image depot.

3.2.3 Homogeneous comparison-based judgement

Considering that the temperature value is inevitably affected by surrounding environments and operating conditions, the temperature difference ($\Delta T$) between the hotspots of homogeneous equipment working at similar operating and environment conditions such as parallel connections or different phases, is a more practicable factor for status evaluation [24]. By considering the environment temperature, the relative temperature difference $\eta$ can be calculated by relation (8):

$$\eta = \frac{\tau_1 - \tau_2}{\tau_1} \times 100\% = \frac{T_1 - T_2}{T_1 - T_0} \times 100\%$$

where $\tau_1$ is the hotspot temperature rise, $T_1$ is the hotspot temperature, $\tau_2$ is the reference spot temperature rise, $T_2$ is the reference spot temperature, $T_0$ is the environment temperature. Table 3 gives fault degree of power equipment based on $\eta$ by Chinese power industry standards DL/T 664-2016 [25]. In addition, there are also some standards such as Inter National Electrical Testing Association [26], American Society for Testing & Materials–E1934 [27] and National Fire Protection

| Fault types                  | Fault equipment | Fault reasons                                      | Temperature rise degree |
|------------------------------|-----------------|---------------------------------------------------|-------------------------|
| Current-induced heating fault| Isolated switch  | Bulk conductivity decrease:                    | High                    |
|                              | Connect unit    | Poor electrical contact                          |                         |
|                              |                 | Insulation deterioration                         |                         |
|                              |                 | Partial short-circuit/dischage                   |                         |
|                              |                 | Surface conductivity decrease:                   |                         |
|                              |                 | External pollution/damp                          |                         |
|                              |                 | Surface damage/deterioration                     |                         |
| Voltage-induced heating fault| Voltage transformer | Dielectric loss increase:              | Low                     |
|                              | Insulator       | Interior damping                                 |                         |
|                              | Lightning arrester| Dielectric ageing                                |                         |
|                              | Capacitor       | Leakage current increase:                       |                         |
|                              | Bushing         | Insulation deterioration                         |                         |
|                              |                 | External pollution/damage                        |                         |
|                              |                 | Semiconductor deterioration                      |                         |
|                              |                 | Local potential increase:                       |                         |
|                              |                 | Winding deformation                              |                         |
|                              |                 | Turn/layer-insulating damage                     |                         |
| Synthetic heating fault      | Transformer body | Electromagnetic effects:             | Low                     |
|                              | Paralleling reactor| Eddy current                               |                         |
|                              |                 | Conduction current                               |                         |
| Non-electrical fault         | Gas insulated switchgear | SF$_6$ leakage                | Depending on the cause of the failure |
|                              | Cooling system  | cooling system failure                          |                         |

Table 2 Classification of typical fault types of power equipment
infrared case maps are given as examples according to the type of equipment and typical faults, as shown in Table 4 out the practical cases in the literature [21, 25, 26, 29], library based on a large number of practical cases. By sorting great significance to construct the typical fault infrared image.  

3.3 Typical fault infrared image cases

Infrared diagnosis relies on the existing experience, so it is of great significance to construct the typical fault infrared image library based on a large number of practical cases. By sorting out the practical cases in the literature [21, 25, 26, 29], infrared case maps are given as examples according to the type of equipment and typical faults, as shown in Table 4 and Figure 3.

3.4 General procedure of thermal fault identification

The general procedure of thermal fault identification is described as Figure 4 based on a great deal of field application experience.

i. Select a proper field of view covering the main object
ii. Locate the hotspots on the specific devices of the object equipment
iii. Evaluate the thermal status by using abnormal temperature rise judgement guidelines described in Section 3.2
iv. Identify the origin of the fault in light of past experiences or match the fault in the image case library

If the equipment is not faulty, the inspection will be completed and the hotspot temperature value will be recorded for could-be historical trend analysis.

There is an example of performing IRT fault diagnosis on a high voltage post insulator being shown in Figure 5 [25]. By acquiring an IR image covering the insulators of the three phases, the hotspot is positively located on the B phase post insulator with temperature value of 26.2°C, homogeneous comparison method is thus adopted in the fault diagnosis. By comparing with the temperature value of the A phase post insulator, the result shows that the temperature rise (ΔT) is 1.3°C. It is speculated that the fault is due to increase of leakage current, which means the B phase post insulator should be replaced immediately.

3.5 Summary

The extensive application of thermal faults diagnosis of power equipment based on IRT has significantly improved the validity of early fault diagnosis and formed a set of effective manual fault diagnosis method. Admittedly, such human-based method can flexibly complete fault diagnosis in complex test conditions, but it is over-reliant on subjective and indescribable experience. In addition, it is difficult to ensure its work efficiency as the number of power equipment increases greatly. Therefore, using machine vision technology instead of manual analysis has become a new development trend. In this process, studies on automatic IRT fault diagnosis has gone through two stages that is machine-assisted fault diagnosis and image-based intelligent fault identification, which will be discussed in Section 4 and Section 5.

4 MACHINE-ASSISTED FAULT DIAGNOSIS

Machine-assisted fault diagnosis, as a kind of semi-automatic method, can replace a part of manual operation in image pretreatment and target detection, and significantly improve the accuracy and speed of image processing. The basic flowchart of machine-assisted fault diagnosis is described by Figure 6. In this section, the principles and the advances of image pre-treatment, image segmentation, target identification, feature extraction and thermal status rating are investigated respectively.

4.1 Image pre-treatment

As aforementioned in Section 2.2, a high quality of infrared image is the promise of effective target identification and fault location. Therefore, prior to target detection, image pre-processing should be performed to suppress the noise, enhance the contrast and improve the image quality.

With regard to noise reduction, mean filtering [30], median filtering [31] and adaptive filtering [32, 33] are commonly used, and a range of advanced algorithms upon them came out with different superiorities [34–36]. Besides, wavelet transform [37], over-complete sparse representation [38, 39], convolutional neural network [40] have also been introduced and greatly improved the accuracy and speed of image de-noising.

4.2 Image segmentation

Image segmentation is the essential element in target extracting, which is performed to divide the image into several specific regions of interest with unique features including grey scale, colour, texture and shape of the image and extract the target of interest [41]. In principle, it can be classified into threshold segmentation, edge detection and region correlation [42]. In addition, there are also some methods based on the roughness, contrast, direction and compactness of adjacent pixels with
### TABLE 4 The radiation coefficient of common materials (Current-induced heating faults—C; voltage-induced heating faults—V; synthetic heating faults—S, and the other faults—O)

| Detection object                  | Faults reasons        | Faults type | Surface temperature | Image feature analysis | Homogeneous comparison | Image Number |
|-----------------------------------|-----------------------|-------------|---------------------|------------------------|------------------------|--------------|
| Transformer                       | Bushing body          | Out of oil  | V                   | ◎                      |                        | (1)          |
| Transformer                       | Bushing general cap   | Poor internal connection | C | ◎                      |                        | (2)          |
| Transformer                       | Bushing outlet clamp  | Poor connection | C | ◎                      |                        | (3)          |
| Transformer                       | Bushing tap           | Poor connection | C | -                      | ◎                      | (4)          |
| Transformer                       | Body                  | Eddy current loss | S | ◎                      | ◎                      | (5)          |
| Transformer                       | Body connection       |             | ◎                   | ◎                      |                        | (6)          |
| Transformer                       | Cooler                | Cooling system failure | O | -                      | ◎                      | (7)          |
| Transformer                       | Oil pillow            | Oil pillow capsule fell off | O | -                      | -                      | (8)          |
| Gas insulated switchgear          | Body earth clamp      | Poor connection | C | ◎                      | -                      | (9)          |
| Breaker                           | Contact               | Poor connection | C | ◎                      | ◎                      | (10)         |
| Breaker                           | Grading capacitor     | Internal damp | V | -                      | ◎                      | (11)         |
| Disconnector                      | Knife edge            | Poor connection | C | ◎                      |                        | (13)         |
| Disconnector                      | Wiring board          |             |                         | ◎                      |                        | (14)         |
| Mutual inductor                   | Upper end             | Out of oil  | V | -                      | ◎                      | (15)         |
| Mutual inductor                   | Body                  | Internal damp | - | ◎                      |                         | (16)         |
| Arrester                          | Electromagnetic unit  | Internal damp turn-to-turn short circuit ferromagnetic resonance | - | ◎                      |                         | (17)         |
| Arrester                          | Damp (bad seal) and ageing | V | - | - | ◎ | (18) |
| Wall feed-through sleeve          | Baseboard             | Eddy current loss | S | ◎                      | ◎                      | (19)         |
| Reactive power compensator        | Shunt capacitor bank  | Internal damp partial discharge | V | - | ◎ | (20) |
| Reactive power compensator        | Shunt capacitor bank fuse | Internal damp poor connection | V | ◎ | - | (21) |
| Reactive power compensator        | Series reactor        | Abnormal voltage internal damp cooling system failure | V | - | - | (22) |
| Reactor                           | Bus                   | Poor connection | C | ◎                      | -                      | (23)         |
| Reactor                           | Paralleling reactor   | Turn-to-turn short circuit poor connection internal damp | S | ◎ | - | (24) |

(Continues)
similar features space clustering [17]. To summarize the efforts made in such field in recent years, some representative examples of infrared image segmentation methods are listed in the Table 5. And an example of IR T imag es segmentation results using various methods is shown as Figure 7 [56].

As the shown in Figure 7, due to the limitations of infrared image, the problem with simple image segmentation methods is over segmented or under segmented. Fusion of segmentation methods is an effective way to solve the problem [43]. For instance, Sobel operator is introduced into the regional growth algorithm as an additional growth condition in the growth criterion, which will effectively reduce the over-segmentation and under-segmentation caused by noise signals and ensure sufficient computing speed. In addition, some morphology and random process such as morphological algorithm [46, 55] and Markov random field [56] are introduced to improve the accuracy of infrared image segmentation.

### 4.3 Target identification

As aforementioned in Section 3.4, an accurate object recognition is the basis of automatic fault location and following diagnosis. In specific realization process, the features of the equipment region in the infrared image should be firstly extracted, and then the prior classifier should be employed to reconstruct the object with the extracted features.

In principle, the essence of feature extraction is to describe the spatial features of high-dimensional images with low-dimensional spatial features by means of mapping [58]. In brief, colour, texture and geometric feature are three most important features for images [59]. However, the colour feature of infrared images corresponds to the temperature distribution rather than the colour information. As a consequence, it is not suitable as the feature in infrared images. The texture feature can accurately describe the device feature depending on the quality of the infrared image, and the typical texture feature is histogram of oriented gradient [59]. With the invariant of rotation, translation and scale, a series of invariants of geometric features such as Hu moments [60, 61] and Zernike moments [62] are used as the equipment feature in infrared image.

An effective classification model is another key factor of target identification, which is generally built via continuous renovation and perfection with the features extracted from
new observation data in the application. In pursuit of the training efficiency and model robustness, two classical classifiers should be mentioned, that is, support vector machine (SVM) [63] and artificial neural network (ANN) [64], which are well recognized in wide applications in practice. The former has better generalization ability and interpretation ability, and is applicable to the optimal solution of small sample space. The latter can have strong nonlinear fitting ability and self-learning ability, which is more suitable for the optimal solution of large sample space. For different research objects and modelling accuracy, the two methods achieve different results.

Table 6 sums up the experiences of infrared image target identification in recent years, which provides various attempts at target identification of different power equipment. It should be pointed out that though feature extraction and target identification has gained some traction, a generic model is still lacking, which is inclusive for diverse infrared image samples in practical use without human intervention.

4.4 Temperature information extraction

For open source infrared imager, it provides a header file with a spatial temperature matrix included, by which the temperature distribution for the region of interest (ROI) can be extracted expediently [68]. But for non-digital imagers still in use and source-restricted commercial imagers, the temperature information of ROI has to be extracted from infrared image directly. As aforementioned in Section 2.1,
the infrared imager converts the temperature information of each detecting pixel into the image with a colour mapping function, which makes it possible to extract the temperature information with a certain fitted function describing relationship between the red-component, green-component and blue-component or grey value and temperature value. Toward this end, linear/nonlinear continuous functions [66, 68] or more complex functions such as piecewise function [69] are utilized. Based on this, the temperature range can be mapped into colorimetric value range, and the ROI can be coded into a spatial temperature matrix. The general process of temperature information extraction is described in Figure 8.

4.5 Thermal fault identification and diagnosis

Thermal fault recognition is the final step of the whole IRT-based fault diagnosis. Based on the premise that the target identification and temperature information extraction are fully completed, the fault recognition can be easily realized by comparing the relative temperature difference $\gamma$ of ROI with the corresponding criteria of standard references [60, 64, 68]. But in reality it is hard to guarantee the confidence of such evaluation by using a single characteristic parameter. On account of the variety of thermal faults of power equipment and the complexity of underlying causes, thermal fault recognition is the step that most dependent on manual intervention and experience transplantation. Even so, the use of machine assistance can still greatly improve the efficiency of diagnosis, and the evolution and application of intelligent algorithms make it possible to replace human labour.

ANN and its extended models have achieved good performance in thermal fault diagnosis [24]. Hongying He et al. (2006) represented a radial basis probabilistic neural network to evaluate insulators thermal condition based on environmental average temperature, maximum temperature of insulator surface, average temperature of insulator surface, variance of insulator surface temperature distribution and humidity factors [70]. C.A.L. Almeida et al. (2009) investigated the potentials of neuro-fuzzy network in classifying the thermal condition of power equipment by material, rated voltage, manufacturer, pollution index, distance, emissivity, etc.

![Flowchart of general diagnosis faults](image1)

**FIGURE 4** The flowchart of general diagnosis faults

![Flowchart of machine-assisted fault diagnosis](image2)

**FIGURE 5** An example of post insulator fault diagnosis

**FIGURE 6** The flowchart of machine-assisted fault diagnosis. IR, infrared
ambient temperature and relative humidity [71]. A probability neural network model with temperature eigenvector as characteristic parameters was constructed to diagnosis the low or zero resistance faults and pollution faults of the insulator string [72]. Multilayer perceptron network was applied to evaluate the equipment condition in reference [73]. Test results of the above networks show that the classification accuracy of these systems can reach more than 80% even 90%.

As a matter of fact, even the intelligent approaches have been adopted, such machine-assisted diagnosis still falls behind practical requirement. The variety of thermal faults of power equipment and the complexity of underlying causes are still the main challenges in reality. At the present stage, machine-assisted diagnosis is proven to be effective for the object with simple structure and single fault cause. In the example of a thermal fault of contact connector studied in reference [4], as shown in Figure 9, the $\eta$ between the A

| Method                  | Model and algorithm                                      | Object                        | Reference |
|-------------------------|----------------------------------------------------------|-------------------------------|-----------|
| Threshold method        | Fuzzy Renyi entropy and chaos differential evolution algorithm | Isolating switch              | [43]      |
|                         | OTSU algorithm and normalized cross correlation (NCC) template matching | Transformer bushing          | [44]      |
|                         | Bi-threshold OTSU algorithm                               | Insulator                    | [8]       |
|                         | Mathematical morphology improved OTSU algorithm           | Insulator                    | [45]      |
|                         |                                                          | Control components for electric machines | [46]      |
| Edge detection method   | Roberts operator                                          | Solar panel connector        | [47, 48] |
|                         | Prewitt operator                                          |                               |           |
|                         | Sobel operator                                           |                               |           |
| Region correlation method| Seeded region growing                                     | Connector                    | [49]      |
|                         | Chan–Vese model                                          | Bushing                      | [50]      |
|                         | Watershed algorithm                                      | Oil pillow                   | [51]      |
| Feature space clustering method | Fuzzy C mean (FCM)                                    | Transmission tower/line      | [52]      |
|                         | Outlier-factor-based cluster analysis                    | Insulator                    | [53]      |
|                         | K-means                                                  | Bushing                      | [54]      |
|                         | K-means and morphological algorithm                      | Current transformer          | [55]      |
| Other methods           | Markov random field                                      | Connector                    | [56]      |

**FIGURE 7** Image segmentation results of bushings of a power transformer.
(a) Original image, (b) Kapoor’s method, (c) OTsu’s method, (d) FCM method, (e) Region growing method and (f) Iterative method. FCM, Fuzzy C mean
phase and C phase is 87%, and the fault degree is determined as major. By matching the temperature rise range and the potential faults causes of contact connector, the thermal fault is accurately recognized as poor connection due to the loosen of bolt. However, for the equipment with multiple fault causes, such diagnosis is inadequate without input of auxiliary information. For example, as shown in Table 4, the overheating fault reasons of the mutual inductor electromagnetic unit mainly include internal damp, turn-to-turn short circuit and ferromagnetic resonance which will lead to the similar temperature distribution on the equipment surface, therefore the fault reason cannot be concluded based on the infrared image alone. To solve this problem, the combination of IRT diagnosis and other various sensing information, such as dielectric loss measurements and moisture content, dissolved gases analysis (DGA) and voltage monitoring is a feasible approach.

### 4.6 Summary

In machine-assisted thermal fault diagnosis, the accuracy fault recognition depends to a great extent on feature extraction and target detection, while the features are still manually selected with means of complex enhancements and segmentations, and traditional target detection is still inadequate to identify multi-category power equipment under complex background. The problems remaining in machine-assisted fault diagnosis, such as weak universality, complicated process and slow recognition speed hinders its extensive use, and thus are expected to be addressed by more intelligent and universal strategies.

### 5 IMAGE-BASED INTELLIGENT FAULT IDENTIFICATION

Compared with traditional target detection, the intelligent algorithms represented by DL have raised the level of target detection and realized image-based intelligent fault identification. The contributions of the intelligent algorithms are mainly reflected in the process of target detection, while the temperature extraction and fault diagnosis are still similar with previous methods. Therefore, this section mainly reviews the application of DL algorithm in target detection.

#### 5.1 Overview of the deep learning

In 2006, the concept of the DL was proposed by Geoffrey Hinton in reference [74]. DL is a representation-learning method with multiple levels of representation, obtained by composing simple but non-linear modules that each transform the representation at one level (starting with the raw input) into a representation at a higher, slightly more abstract level [75]. Compared with traditional learning algorithms such as SVM, DL is a data driven method without the process of manual feature extraction. Due to the use of
complex models, depth features have more accurate and general expression ability [76]. DL technique has been widely applied to identify objects in transcribing speech into text, match news items, posts or products with users’ interests, and select relevant results of search, especially in image target detection [75]. The typical DL net structure includes Deep Belief Network, CNN, recurrent neural network and Capsule Network (CapsNet). Among them, CNN and its extended framework have made great achievements in the area of image processing [77].

In terms of network architecture, CNN is a kind of deep feedforward network and the basic structure consists of input layer, multiple convolutional layers, multiple pooling layers, full connection layer and output layer. The basic structure of the CNN is shown as Figure 10 [78].

5.1.1  |  Input layer

It is the gateway to the entire network for data input.

5.1.2  |  Multiple convolutional layers

In these layers, the input data will be extracted with the convolution features by the convolution kernel (also called filter). Then the results will be nonlinear mapped through the activation function to generate the 2-dimension feature maps and stack along the depth direction to obtain the output data body of the convolutional layers. Commonly used activation functions include the Sigmoid function, Tanh functions and the Rectified Linear Unit (ReLU).

5.1.3  |  Multiple pooling layers

Pooling layer is to combine the response values of the feature maps based on pooling function, so as to realize the reduction and abstraction of the convolutional features, which can reduce the space size of the feature maps and the amount of network computation. Common pooling functions include the average pooling function and the maximum pooling function.

5.1.4  |  Full connection layer

Full connection layer integrates and classifies the features after multiple convolution and pooling operations.

5.1.5  |  Output layer

It is the outlet for classification results.

In this study, the application of CNN and its extended structures in infrared image processing of power equipment will be introduced. Due to the topic of this study, more details about the background knowledge and the basic network architecture of CNN can be referred to literatures [75, 77, 79].
5.2 CNN-based target detection on IR images

There are two frameworks for CNN-based target detection methods used in IR image processing [77]:

i. Two stage detection framework, or region proposal framework. In such framework, a pre-processing for building category-independent region proposals from the image is carried out before the CNN features can be extracted from the proposals, and then the labels of the proposals can be determined by classifiers. The representative algorithms are Region-based CNN (R-CNN), SPPNet, Fast R-CNN, Faster R-CNN, Region based Fully CNN, Mask R-CNN and Light Head R-CNN. These methods are satisfactory in terms of the detection accuracy but they will inevitably take lots of computing resources and processing time.

ii. One stage detection framework, or region proposal free framework. This framework supports making the overall pipeline in only one stage without separation of detection proposal. In this framework, CNN is proposed as a regression device, and the whole image to be detected is regarded as a candidate region. By directly inputting the image into the convolutional neural network, the position information of the target in the image can be detected. The representative algorithms include DetectorNet, OverFeat, You Only Look Once (YOLO), YOLOv2, Single Shot Detector, YOLOv3, most of which are usually superior to the first framework methods in term of detection speed.

To further understand the applications of CNN on IRT image target detection, some latest research advancements for practical use are demonstrated as follows.

In 2017, Zhenbing Zhao et al. [10] presented a deep CNN feature extraction strategy and vector of locally aggregated descriptors (VLAD) feature map aggregating method for insulator strings detection in infrared images, as shown in Figure 11. Different from the conventional CNN-VLAD method, this network extracted deep activations from convolutional feature maps of infrared insulator and modified the deep feature extraction framework by replacing the last three full connection layers with the VLAD pooling layer, finally an SVM classifier was trained for infrared insulator classification and detection. Compared with the previous work, this method greatly enhances the invariance of deep features and achieves the extraction of deep features.

Similar work has been reported in the literature [80]. The authors achieved the identification accuracy as 99.9% on seven types of equipment, that is, insulator strings, lightning arrester, circuit breaker, current transformer, capacitor voltage transformer, disconnecting switch and high voltage bushing, by inputting 4119 samples into a CNN model with 10 layers.

In 2018, an automatic segmentation and recognition system for IRT images of power equipment based on CNN was reported, in which, a segmentation method named JSEG was used to extract the overheat spots, and YOLO network was applied to identify the equipment type of the hotspots [81].

Xiaojin Gong et al. also reported a deep CNN based on YOLO for power equipment detection in thermal images [82]. The overview of the model is shown as Figure 12. The deep CNN took an IRT image as input and output both oriented bounding boxes and associated class probabilities, followed by a non-maximum suppression step to obtain final detection results. This model overcomes the decrease of identification accuracy caused by orientation changes and eliminates the background noise by predicting boxes tightly bounded instead of simple upright bounding boxes. In addition, this model realizes the prediction of the coordinates, orientation angle and class type of each equipment part from the complex scenarios.

In 2019, Li Lianqiao et al. realized target detection and automatic readout of the temperature value of the hottest spot based on YOLO [83]. In addition, authors compared its recognition accuracy and processing speed with R-CNN-based model. The results showed that in spite of the slight loss of the recognition accuracy, introduction of YOLO can significantly improve the recognition speed of IRT image target.

To enhance feature extraction ability and improve target positioning accuracy, Guangjun Yang introduced a Faster R-CNN based on Feature Pyramid Network model, which expressed good potential in solving the small target detection of the infrared image and demonstrated a considerable identification speed at 15 frames per second on graphics processing unit for streaming media applications [84].

In 2020, Mask R-CNN was first introduced by our research group in instance segmentation, by which the outlines of objects are predicted at the pixel level and the different objects belonging to the same category are distinguished [68]. The principle of Mask R-CNN-based instance segmentation for insulator infrared image is shown in Figure 13.

To address the Small Sample Size (SSS) problem which is the most common causes of training failure, we adopted the transfer learning method to complete the preliminary training of Mask R-CNN model. Thereinto, the Common objects in context dataset was tailored with limited amount of annotated
infrared images; while the other infrared images were used as the verification set and testing set to determine the Mask R-CNN weight. The design and flowchart of the instance segmentation process for infrared images was shown as Figure 14. In fact, in the training process of neural network, the adjustment of network parameters still depends on the participation of human experience, such as learning rate, number of hidden units, mini-batch size, training strategy, number of iterations per epoch and so forth. Therefore, when the sample size is small, manual intervention has a direct impact on the network precision.

With the high quality of the instance segmentation, the temperature distribution of the target could be easily obtained by converting the temperature grey value into temperature
matrix by function fitting. Figure 15 shows a practical diagnosis case of an insulator. The main steps to realize the automatic fault diagnosis can be described as follow:

First, by using a trained Mask R-CNN model, the instance segmentation will be realized from the original infrared image and the mask region coordinates will be returned, as Figure 15a, b.

Second, the temperature information will be extracted from the pixels of the insulator mask, as Figure 15c. By image greying, the false colour information of mask areas is converted to grey values, as Figure 15c (1) to (2). On this basis, the temperature value will be fitted by grey values of every pixel of mask areas, as Figure 15c (3) and (4).

Finally, the insulator was thought as in fault state according to the abnormal temperature value, and the potential fault cause was considered to be transverse or longitudinal cracks combined with the information of temperature distribution.

5.3 | Summary

Image-based intelligent fault identification, as a data-driven feature extraction method, has a more accurate and general expression ability compared with semi-automatic method. It can extract power equipment accurately under complex
background and the simultaneous recognition of multiple types of equipment. However, due to the accuracy and generalization ability of these models depended on the equipment infrared dataset whose establishment requires a great deal of manpower and time, the performance of the existing target detection models still cannot reach the level of manual recognition. At the same time, with the models being more complicated, it requires a greater supply of computing power by hardware.

6 FUTURE RECOMMENDATIONS

With the increase of manpower cost and the expansion of system scale, automation and intelligence are the inevitable trend of the development of IRT of power equipment. In this study, the development of IRT is summarized, and several mainstream intelligent methods are described. This section provides the following suggestions for the future application and engineering practice based on the particularity and speciality of power equipment:

6.1 Construction of intelligent infrared detection system

Whether the application of the machine-assisted method or the image-based intelligent method, the large-scale models and operations require huge computational power beyond the capacity of portable or online monitoring devices. To benefit from cloud computing and edge computing technologies which open up a new solution in terms of computing force distribution and storage resource sharing, the intelligent IRT diagnosis is expected to achieve higher efficiency as well as processing speed with limited local hardware resources [85]. A framework of the future edge-cloud synergetic intelligent IRT diagnosis system can be drawn as Figure 16.

6.2 Establishment of an open and shared infrared image database

Like machine vision applications in other industrial and consumer markets, the development and application prospect of the IRT are strongly dependent on the openness and data sharing by manufacturers and users. Therefore, an ideal data ecocycle should be established by the open access of the real data interface and software development kits provided by IRT device manufacturers, and a large amount of infrared fault cases provided be power equipment managers.

6.3 Comprehensive utilization of joint visualization diagnosis technology

As mentioned as Section 4.5, the thermal fault of power equipment is a comprehensive result by various underlying causes, which are accompanied with other physical phenomena, such as electrical discharges and mechanical vibrations and can be reflected in a specific range of optical or acoustical spectrum, as shown in Figure 17. It is believed that in the foreseeable future, the knowledge dimensionality on fault diagnosis can be significantly improved by adopting more visual perception technologies [76, 86–89].

7 CONCLUSION

In this study, we reviewed the IRT-based fault diagnostic on power equipment from its development history to recent advances. As the motive force of development, the rapid growing number of equipment in power grid necessitates the replacement of manpower with automatic and intelligent technologies. Following the evolutions of image processing algorithms and hardware computer power, the development of
IRT-based fault diagnosis went through two stages, that is, machine-assisted (or semi-automatic) fault diagnosis and image-based intelligent fault diagnosis, both of which render the great potential to replace a part of manual work even the whole in infrared image analysis. In this review, we attempted to sum up the experiences to answer the two critical questions, that is, how to use the image processing technology to extract the thermal status of the power equipment from the infrared image, and how to tell the fault causes with apriority and new knowledge mined from the temperature distribution information.

To solve these questions, the technical essentials including image pre-treatment, image segmentation, target identification, temperature information extraction and thermal fault recognition have been linked into a generic procedure for manual,
semi-automatic as well as intelligent IRT diagnosis. It should be mentioned that the algorithms involved in such procedure, especially for image segmentation and target identification, are not dedicated to infrared image analysis, thus should be tailored to apply to low resolution infrared images and targets in complex background.

With the advent of the DL algorithms represented by CNN, the image-based intelligent fault identification has been inspired in recent years. Such data-driven method provides a fully automatic feature extraction without human interventions. Compared with the conventional approach, target detection based on depth features was proven to have higher accuracy and stronger generalization ability. However, the limited local computational power and the small sample size of the infrared image cases are the major bottlenecks that prevent the widespread use of the intelligent IRT diagnosis on power equipment. On the face of this case, more efforts are required to improve the algorithm efficiency of intelligent IRT diagnosis and to establish an open and sharable infrared image database in the future.

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