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Recursive construction of output-context fuzzy systems for the condition monitoring of electrical hotspots based on infrared thermography

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ABSTRACT

Infrared thermography technology is currently being used in various applications, including fault diagnosis in electrical equipment. Thermal abnormalities are diagnosed by identifying and classifying the hotspot conditions of electrical components. In this article, a new recursively constructed output-context fuzzy system is proposed to characterize the condition of electrical hotspots. An infrared camera is initially used to capture the thermal images of components with hotspots, and intensity features are extracted from each hotspot. The Recursively Constructed Fuzzy System (RCFS) is then applied to automatically realize and formulate the conditions of the thermal abnormalities. On the basis of the priority level, the hotspot conditions are categorized as normal, warning, and critical. From these three categories, the conditions can be further simplified into two categories, namely, defect (warning and critical) and normal. The proposed RCFS realizes the prominent distinctions in the output domain by using a self-organizing method. The termination of the recursive algorithm finds an effective rule base to achieve an accurate representation of the datasets. The proposed system obtains less fuzzy rules with reasonable accuracy. Our survey of 253 detected regions shows that the proposed RCFS produces 92.3% and 80% testing accuracies for classifying conditions into two and three classes, respectively. The thermographic diagnostic evaluation shows that the proposed intelligent system automatically identifies the rationally acceptable limits of hotspot conditions. Therefore, the proposed system is suitable for establishing an intelligent defect analysis system.

1. Introduction

Heat energy is an important factor in electrical equipment for increasing operational reliability. Electrical current passes through a resistive component and generates heat. The thermal energy generated from an electrical component is directly proportional to the square of the current passing through it and its resistance (I^2R loss). Therefore, an increase in resistance results in an increase in heat. Over time, the condition of the electrical components will begin to deteriorate because of various reasons, such as poor or dirty connections, overloading, insulation problems, load imbalances, corrosion, and wiring mistakes (Korendo and Florkowski, 2001). Components show increased resistance and heat generation with increasing deterioration. The increase in heat energy can cause electrical equipment to fail and fires to break out. The faults caused by the abnormal heating effect can be prevented if heat is detected at an early stage by effective screening and if necessary steps are immediately taken.

Infrared thermography (IRT) senses the heat produced in electrical components. The thermal profiles of different electrical components and connectors are captured by using an infrared camera. The thermal profile (i.e., thermogram) consists of a heat picture and a scale of the temperature values of the equipment. The different colors of the temperature scale represent the different temperature zones in the equipment. By using this profile, thermographers analyze the thermal images and classify the condition of hotspots on the basis of the priority level of repairs. The thermographers then provide suggestions for further action. Finally, the components with hotspots are tested and repaired according to the priority level (Huda and Taib, 2013).

Both manual and Automatic Feature Extraction (AFE) methods are currently employed for the intelligent classification of the thermal

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conditions of electrical equipment on the basis of thermography. Almeida et al. (2009) proposed an intelligent fault diagnosis system based on thermography for lighting arrestors by using 2 types of variables as inputs of a neuro-fuzzy network. Thermographic and identification variables were used to classify the faults, and the results show approximately 90% accuracy. In one study, RGB color scale data and temperature data were used as the input features of Artificial Neural Network (ANN) to detect internal faults (Shafi'i and Hamzah, 2010). The experiment obtained a 99.38% testing accuracy. Smedberg (2006) and Wretman (2006) proposed an intelligent classification system based on ANN to diagnose 3-phase fuses and different forms of connection problems. The 4 input parameters of ANN were used, namely, absolute max temperature, relative max temperature, mean temperature difference compared with the other regions of the image, and histogram distance to the other regions of the image. The test error rate was 9.5% when all 4 feature parameters are used as ANN inputs, and the error rate was 31.2%when only histogram distance is used as input. The dataset comprised 74 infrared images. One of the disadvantages of working with a small dataset is that the reliability of the results can sometimes be questionable.

On the contrary, several studies have been conducted on the basis of the AFE method and intelligent classification system. Nazmul Huda et al. (2012) proposed a semi-automatic system for electrical thermography. This system uses 15 statistical features and Multi-Layer Perceptron (MLP) network to classify thermal conditions as normal, warning, and critical. This system achieved 78.5% accuracy. Another research proposed an intelligent system to detect faults of electrical equipment in ground substations based on Support Vector Machine (SVM) as a classifier and 22 image features of Zernike moments. The diagnosis obtained 68.42% accuracy (Rahmani et al., 2010). In one study, 10 statistical features and MLP network were employed to differentiate between normal and defective conditions. The system achieved 82.40%accuracy (Nazmul Huda and Taib, 2013). In another study, 6 statistical features and MLP network were used to identify the overheated component; the system reached 79.4% accuracy (Huda et al., 2014).

To develop a robust and reliable system, a new Recursively Constructed Fuzzy System (RCFS) is introduced in this study to classify the conditions of hotspots in components. The proposed system employs AFE and a novel intelligent classification system. The gray scale images of infrared thermal images of components are segmented by using a manual thresholding technique. Then, AFE system automatically extracts six intensity features (i.e., maximum, minimum, mean, median, standard deviation, and variance). The RCFS is a self-automated system that automatically detects the conditions of components and classifies the abnormalities of electrical equipment into classes, namely, normal, warning, and critical. In this study, the RCFS is an output-context fuzzy system that recursively constructs the fuzzy rule base by determining the prominent distinction on the output domain. The termination criterion for recursive algorithm is not threshold as presented in Wang et al. (2010), which realizes from previous and present stages of evolving. The algorithm terminates by recognizing the overfitted partition of the system; therefore, an effective rule base is obtained by the proposed RCFS. After termination, a further evolving process will decrease the model performance. Hence, the computational model of the fuzzy system is automatically designed by the RCFS rather than by human experts.

Neural fuzzy systems are hybrid systems that capitalize on the functionalities of fuzzy systems and neural networks (Nauck et al., 1997). The black-box nature of a neural network can be resolved by integrating the interpretability of a fuzzy system into a connectionist structure (Nauck et al., 1997; Tung et al., 2011). Furthermore, introducing the learning capabilities of a neural network into a fuzzy system will enable the system to automatically refine its parameters (Bosque et al., 2014; Tung et al., 2011). The output-constrained cluster approach (Wang et al., 2011) and Semantic Cointention (SC) approach (Mencar et al., 2011) consider the fuzzy c-means (FCM) to partition data. In the output-constrained cluster approach (Wang et al., 2011), the output space is first roughly partitioned by using FCM. Thereafter, the data within each output constraint are further refined on the basis of "separability," which refers to the connectivity of the inputs. Prior knowledge of rough clustering in the output space makes a fuzzy system unintelligent. The results in Wang et al. (2011) and Mencar et al. (2011) are highly subjective and uncertain because prior knowledge (user-defined number of clusters) was used to design these fuzzy systems. The results are subjective in the sense that the user-defined numbers of clusters are applied to the environment. Nonlinear training or testing errors can be observed in the evaluation, and an absence of overfitting/underfitting assessment is present. Therefore, uncertain results (nonlinear training or testing error) are obtained for some clusters. For example, based on Mencar et al. (2011) for the ionosphere dataset, a nonlinear nature of the testing errors is observed while number of cluster increases. For the automobile dataset, Wang et al. (2011) shows that the training error increases and the testing error decreases with increasing number of rules. Nevertheless, inconsistent results between automobile and census datasets were found. The output domain is evenly partitioned similar to the method of Pedrycz and Kwak (2006); therefore, the output domain ignores the local distribution of the input data. An evenly partitioned output domain may also cause underfitting or overfitting, therefore leading to inaccurate performance. The aforementioned limitations of the existing models are considered in the RCFS. The RCFS is a self-organizing process and evolves by considering both the input and output spaces. The evolving process continues until the termination criteria are fulfilled and the RCFS successfully obtains an effective rule base.

The remainder of this paper is organized as follows. Section 2 describes the necessity of IRT for fault diagnosis. Section 3 discusses the methodology of thermographic diagnosis. Section 4 covers the AFE technique. Section 5 elaborates on the RCFS and its algorithms. Section 6 evaluates the expert system for thermographic diagnosis of electrical components. Section 7 concludes.

2. Importance of infrared thermography-based condition monitoring

The infrared camera is a device that displays the surface temperature of an object by detecting the infrared energy radiated from the surface of this object. The IRT technique is an early internal and external fault diagnosis system for electrical components and provides various advantages over conventional thermal condition and fault diagnosis tools (Kregg, 2004). Some of the advantages of the IRT diagnostic system are described as follows.

2.1. Preventive/predictive maintenance

To maintain electrical equipment, two types of approaches (run-to-failure or preventive maintenance) are used. The run-to-failure approach is simple and straight forward. This approach does not involve an outflow of money for maintenance before the eventual failure of the equipment. The approach waits for equipment failure before any action is taken for maintenance. Therefore, this method is more expensive than preventive maintenance. By contrast, a thermography-based diagnosis system allows preventive/predictive maintenance for the early prevention of equipment failure without interrupting running operations, thus saving money. According to historical data in the United States (TBPPM, 2011), the effective use of preventive/predictive maintenance will