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Development of thermographic module for predictive maintenance system of industrial equipment

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Abstract

The maintenance of industrial equipment extends its useful life, improves its efficiency, reduces the number of failures and increases the safety use. This study proposes to develop a predictive maintenance tool based on infrared thermographic measures capable of anticipating failures in industrial equipment. The thermal response of selected equipment in normal operation and in controlled induced anomalous operation was analyzed. The characterization of these situations enabled the construction of a machine learning system capable of predicting future malfunctions.

1. Introduction

The maintenance of industrial equipment, machine or facilities tends to extend its useful life, obtain a correct performance for a longer time, improve its efficiency, reduce the number of failures and increase the safety in use. Maintenance management has evolved considerably over time. Progress has been made from applying corrective maintenance, where the equipment failures are solved when they occur, to applying a preventive maintenance, where the equipment is periodically reviewed and certain components are replaced based on statistical estimates, often provided by the manufacturer, up to the current tendency of applying predictive maintenance, which tries to predict the failure of a component, such that the component can be replaced before the failure occurs.

A new predictive maintenance technique that is gradually spreading in the industrial sector is the infrared thermography (IRT) based technique [1]. The vast majority of failures in industrial equipment and machinery are preceded by temperature changes that can be detected by monitoring with an infrared thermographic system. Thermal data collected with a thermal sensor can be a very valuable source of information and can identify problems at an early stage so that they can be registered and corrected before getting worse and more expensive to repair. Although the characteristics of the IRT make it applicable to multiple areas of predictive maintenance and provides many advantages over other techniques, its scope is still quite limited at the moment. Infrared Thermography has enormous potential as a predictive maintenance tool for equipment and facilities [2-5]. However, currently its use is mainly aimed at detecting existing faults, rather than a true predictive strategy that anticipates the occurrence of failures.

Another emerging technology that has already proven its effectiveness in industrial maintenance is augmented reality (AR). Among the multiple advantages of this technology in the field of equipment maintenance, it is worth mentioning the reduction of the costs associated with the acquisition of operation and repair skills, as well as the reduction of the risks associated with the technical personnel by guiding the execution of the maintenance tasks more accurately. The present study proposes to develop a predictive maintenance system based on the potential of infrared thermography technology, which incorporates a set of functionalities and tools based on innovative technologies, such as augmented reality, machine vision and machine learning, to properly manage thermographic measures, automatically analyze the data obtained and advise in advance about a possible failure before it occurs.

2. Description of MANTRA System and its Components

The functional architecture of the MANTRA system for predictive maintenance through intelligent thermographic analysis, is established on the integration and interrelation of the following 3 systems.

2.1. Reference Thermal Model

Thermal modelling is integrated in the MANTRA system to provide theoretical thermal states of the systems under maintenance. The subsequent comparison of the modeled states with the ones captured by the thermographic system enables to identify malfunction conditions even predict future failures. The reference modelling for the electronic components was based on conjugate heat transfer (CHT) method [6], which is a type of heat transfer analysis between solids and fluid(s) that includes both convection (between fluids) and conductive (between solids) heat transfer, as well as both forced and natural convection.

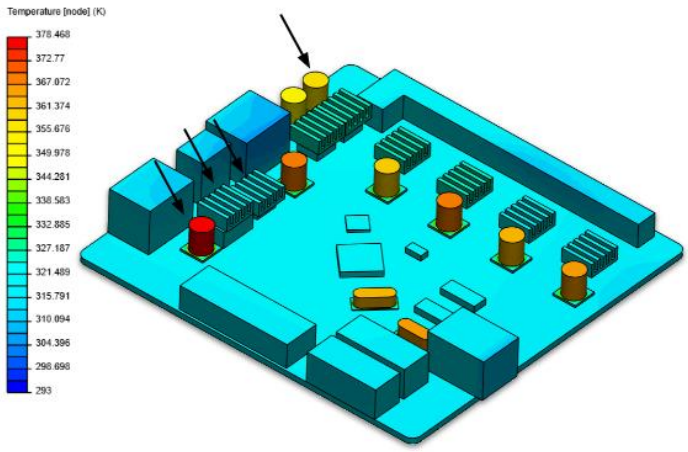

Fig. 1. *Results from the CHT simulation for an electronic board.*

This technique involves several steps. A simplification of the components is necessary, considering that large sections of electronics packages have little influence over thermal performance, including bus plugs, pin connectors, etc. It is critical that every CHT simulation has a solid CAD body that represents the fluid volume. Then the materials are assigned to the different components that form the electronic component, where the most typical are copper, ABS plastic and aluminum. The last material is the printed circuit board (PCB), often a composite material but usually the simulation programs characterize it in a generic way as an anisotropic thermal conductivity property, having high influence in the calculations. Finally, the flow boundary conditions simply indicate what is happening at the system boundaries. For this purpose, it is necessary to define the inlet and outlet faces in terms of speed, temperature and pressure. For the inlet, a flow velocity as well as a temperature of the incoming flow is assigned. For most simulations where the flow velocity is defined at the inlet, the output side should be set to a pressure gauge 0. The solver then calculates the resulting velocity profile and temperature, and sets the thermal load limit conditions for all chips and capacitors in the system.

2.2. Augmented Reality Module

This module has two main components: the graphical unit interface (GUI) and the pose estimation engine. The graphical unit interface GUI has been programmed using the Unity graphical engine. The GUI guides the user through maintenance protocols using detailed using instructions (figure 2), with animated CAD media and controlling the augmented reality module.

Fig. 2. *From left to right: Main GUI, CAD related info and augmented reality vision.*

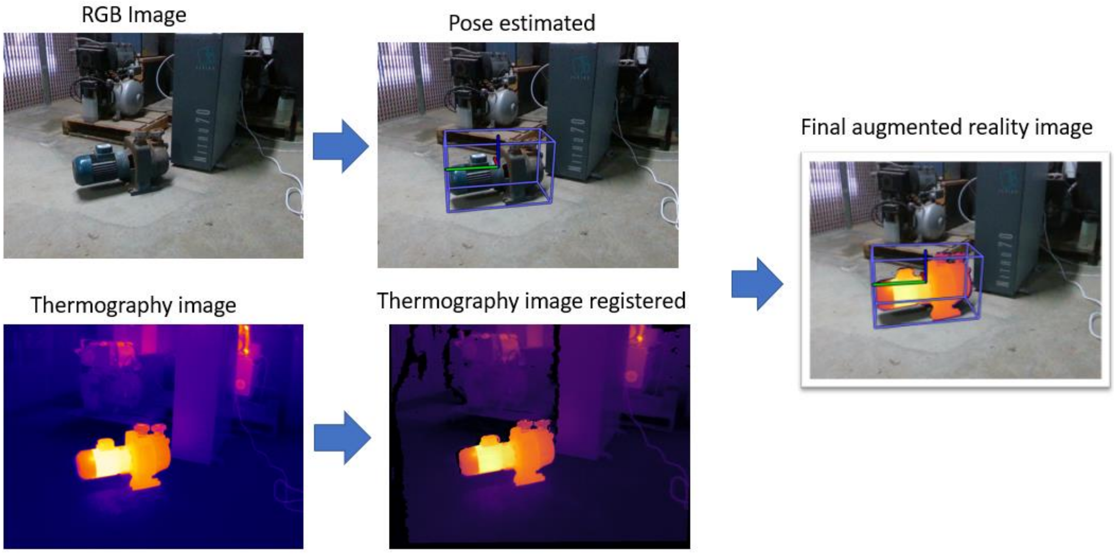

***Fig. 3**. Augmented reality engine flowchart.*

In augmented reality applications it is fundamental to have an accurate and fast pose estimation algorithm to be useful and realistic for a user. The method employed for the pose estimation engine was the algorithm implemented in [7]. This method is based in an optimized version of the template matching algorithm known as LINEMOD with a refinement step using Iterative Close Point [8]. This method works at around 32 fps and achieves a 96.5% AD metric employing the Linemod dataset [9].

The augmented reality engine is also able to show the temperature of specific objects automatically thanks to the registration between the RGB-D camera and the thermographic camera. This registration was performed calculating a stereo geometric calibration between the RGB camera and the thermographic sensor employing the classical Zhang method [10]. This augmented thermal information is depicted in figure 3.

2.3. Thermographic Module

The thermographic module is the sensitive part of the MANTRA system that detects anomalies from a thermal perspective. It tries to identify fault initiations based on changes in thermal behaviors to relate them to present and future failures. The thermographic module records the transient heating process of the equipment under maintenance, and allows the visualization of images in the established intervals, as well as the results of the subsequent analysis.

The infrared (IR) camera used in this analysis was a Xenics Gobi-640-GigE model. This thermographic camera incorporates an uncooled microbolometer sensor that works in the 8 μm to 14 μm spectral band with a spatial resolution of 640 x 480 pixels and 50 Hz of maximum frame rate. The size of this camera (49 x 49 x 79 mm^3) and its weight (263 g) make it suitable to be assembled in a portable device for carrying out maintenance inspections of industrial equipment (figure 4).

The inspections conducted by the thermographic module are passive, i.e. no additional thermal stimulation is applied to the inspected object but the normal operating conditions produces heat that is detected by the IR sensor. The data captured by the thermographic camera is analyzed using processing techniques, such as spectral and statistical analysis, to enhance the thermal features and enable to identify existing anomalies.

***Fig. 4**. IR camera used in the MANTRA system (left) and prototype design of the MANTRA hardware (right).*

Fig. 5. *Study cases: hydraulic pump (left) and swing gate control panel (right).*

The thermographic module includes a verification system that takes the results produced in the analysis of the thermal data captured during the inspections, together with the data produced by the reference thermal model, and classifies them into specific defect or malfunction categories. This classification system is based on machine learning models that have been trained with intentionally caused and controlled induced defective situations. The following sections details the process followed to develop the verification module.

3. Development of the Verification Module

3.1. Definition of the Machine Learning Model

Two different equipment have been analyzed: a hydraulic pump and an electronic board (figure 5). The hydraulic pump is a conventional refrigeration system powered by an induction motor that carries water to hydraulic pipes. The pump is a PRINZE model and works at 2800rpm connected to 380V triphasic line. The electronic board is a EURO230M2 model specifically used in automatic gate opening systems. This board works connected at 220V monophasic line and commands 2 drives that produce the movement necessary to open the gates. To simulate these opening drives a pair of variable resistors adjusted to consume an amount of active power similar to the real drives were connected to the board.

The primary information available for classification issues is the original thermographic image sequence captured by the IR sensor during the inspection. There exist machine learning models able to deal directly with images such as convolutional neural networks [11,12], which are considered the current cutting edge in machine learning techniques. This type of classification systems takes images as input data and after internal computations in the hidden layers of the network, it produces the classification result in the output layer. Unfortunately, this type of machine learning technique requires high deal of study cases to train the classification system, generally thousands of samples for each study case, and the limited scope of this study makes it impractical to produce such amount of data. Additionally, the time spent in the computation for this type of model is high and the premise considered in this study to reduce the computational cost made this classification option to be discarded.

The alternative to the original IR input images for classification issues is the use of features. These features consist of values of specific parameters taken from the captured images that represent the behavior of the analyzed elements and enable to distinguish and characterize them. Many different parameters may be used as classification features such as geometric parameters, signal characteristics or statistical metrics. In this study, the equipment has been inspected by passive thermography under different operating conditions and those areas with most informative contents have been identified for features extraction (figure 6).

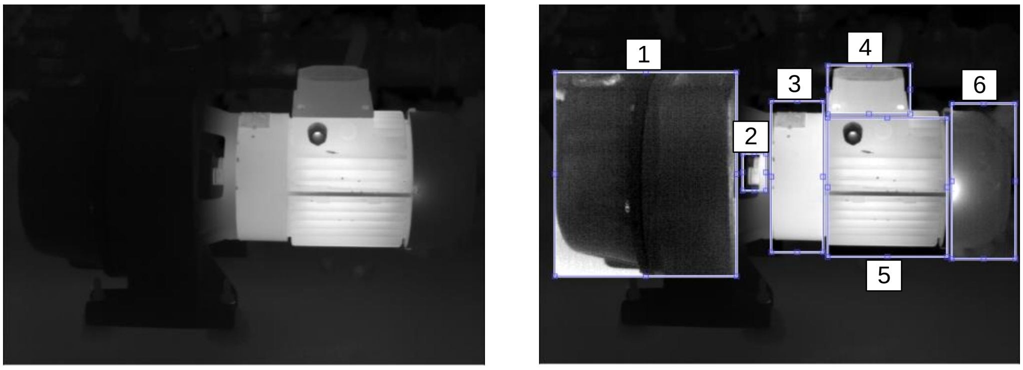

Fig. 6. *Thermal images of the pump normal function (left) and areas used for features extraction (right).*

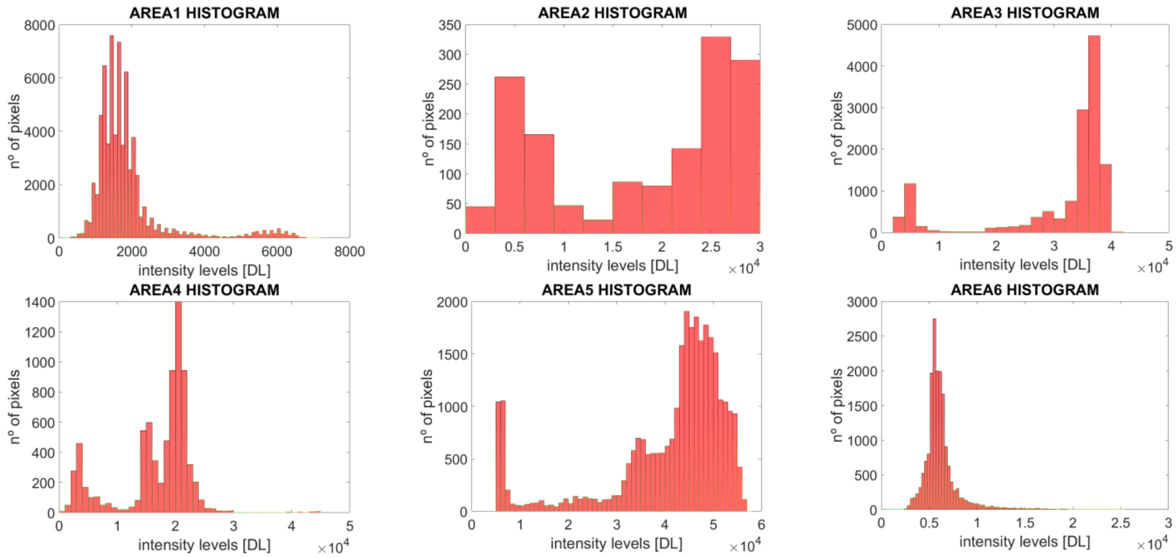

Fig. 7. *Analysis of the featured areas selected in the hydraulic pump by histograms.*

Afterwards, statistical parameters were calculated for the selected featured areas (figure 7). Different parameters were evaluated, including relative maximum and statistical moments like mean, variance, kurtosis and skewness. Among these parameters, those with highest performance for classification purposes were the maximum and variance values. Finally, the results obtained in the previous thermal characterization stage were used to feed a supervised machine learning system capable of automatically classifying the type of anomaly detected by the thermographic system.

Considering the premise of limiting the computational cost to maintain high performance of the whole MANTRA system, the k-nearest neighbours (KNN) algorithm was selected as classification model [12,13]. The KNN is a simple, easy-to-implement machine learning algorithm that can be used to solve both classification and regression problems. The k-nearest neighbour is a semi-supervised learning algorithm such that it requires training data and a predefined k value to find the k nearest data based on distance computation. If k data find different classes, the algorithm predicts class of the unknown data to be the same as the majority class. Figure 8 shows the concept to find the appropriate class of new datum, represented by a green triangle, using the k-nearest neighbour algorithm with a Euclidean distance metric. Different class will be predicted depending on the number k.

In this study, the number of neighbors k has been chosen so that it is large enough to have stable predictions, avoiding outlier effects and overfitting, and at the same time small enough to avoid underfitting and produce increasing computational cost. The number k = 5 was selected experimentally, odd number to avoid draw situations.

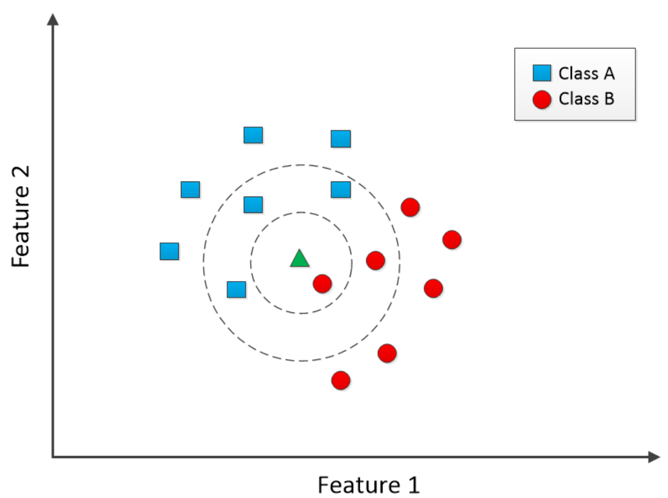

Fig. 8. *Example of KNN classification algorithm for k=1 and k=5 with Euclidean distance.*

3.2. Implementation of the Model to the Electronic Board

The KNN model described in the previous section was implemented with the experimental data obtained from the thermographic inspections of the equipment during different operating conditions. The position of the areas selected for extraction of features in the electronic board is shown in figure 9. Five different features were identified as the most informative points in the board and capable of predicting failures and malfunction situations.

The study cases considered for the electronic board were the following ones:

- reference state: the case corresponding to the correct function that is used as the reference state. The board was programmed to complete the electro-mechanical process in 5 seconds by pressing the operation button.
- bad contact in input connector: this malfunction was induced by producing damage and release in the wires attached to the input connector. This type of malfunction produces local overheating that eventually causes the break of the connector or the affected wire with the total interruption of service.
- bad contact in output connector: like the previous case, bad contact in output connector was induced by producing damage and release in the wires but in the output connector. Two different output connectors exist so 2 different malfunction options are related to this case.
- output overload and underload: these malfunction cases correspond to irregular operating conditions caused by different failures in the output loads. At laboratory level these cases were simulated by reducing and increasing the resistors connected to the board, and therefore the operating current flow, while in real situations they could correspond to mechanical misalignments, excessive friction or disconnections in the gates system. Eventually, these malfunction situations would cause the break of the electric motors commanded by the board.
- fuse failure: this case is produced by the break of a fuse and, contrary to the previous cases, requires corrective actions rather than predictive. This failure prevents the device from working properly and enabling output current. There are 2 fuses in the board so the current failure is produced in a different output depending on the fuse broken.
- relay failure: this case is produced by the malfunction of a relay, induced by avoiding the relay contacts to join correctly. This case also requires corrective actions and the apparent effect to the system operating conditions is the same as in the fuse failure case, i.e. it avoids the output current. There are 2 relays in the board so 2 different relay failures are possible.

Twelve study cases have been defined for classification with the KNN model. These cases were intentionally induced in the electronic board at laboratory level, each one separately, and a test campaign was conducted to capture the thermographic image sequences from which the features were extracted. A total number of 20 tests per study case was carried out so 240 thermographic sequences were obtained.

The features to characterize these cases were obtained from 5 different areas positioned as shown in figure 9. The identification of these areas was carried out by previously analyzing the spectral response of the recorded thermographic sequence for the reference state. These areas correspond to the zones that undergo the main thermal variations during the operation of the board, and they were located in the positions of the fuses (areas 1 and 2), the input and output connectors (area 3) and the output transistors (areas 4 and 5).

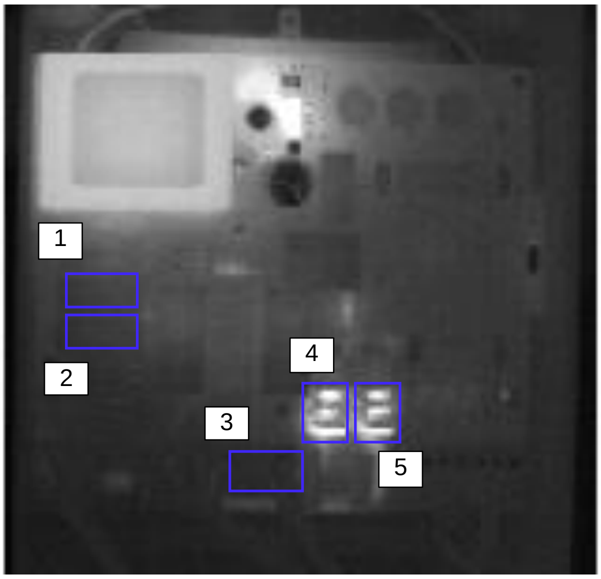

Fig. 9. *Areas in the electronic board selected for features extraction.*

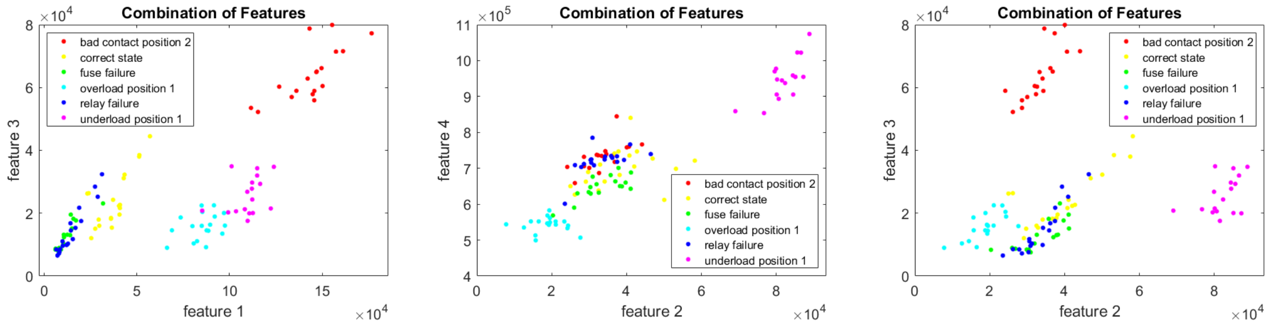

Fig. 10. *Scatter plots for different combination of features identified by the corresponding class.*

Already in the initial spectral analysis, it was detected that some cases produced very similar responses so the distinction among them was not evident. Not all the features uniquely represented each defect, but certain features were common to several failures. A detailed analysis of the features grouped in pairs enabled to identify that, as anticipated in the spectral analysis, many features had close tendencies for different study cases. In figure 10 it may be observed that fuse failure and relay failure had very similar behavior for the 3 groups of features shown. Additionally, for various combinations of features, the correct state and bad contact in output also produced responses similar to relay and fuse failures. On the other hand, the overload, underload and bad contact were clearly recognizable and distinguishable.

3.3. Analysis of the Prediction Capabilities

Different KNN models have been implemented by training them with reduced number of features to obtain the simplest system capable of correctly predicting the study cases. Models implemented with number of features from 2 to 5 were produced. Afterwards, the different models were evaluated by a new set of 18 tests containing 3 samples for each type of failure.

It was verified that the implementation of the KNN model with only 2 features obtained relatively lower success levels in the predictions (70%) and produced confusions among different failures depending on the specific featured used (figures 11a, 11b and 11c). The implementations of the KNN models with 3 features improved the prediction success up to 85% in specific combination of features (figure 11d). Finally, it was verified that using all the features the implemented model predicted the cases with a total success (figure 11e).

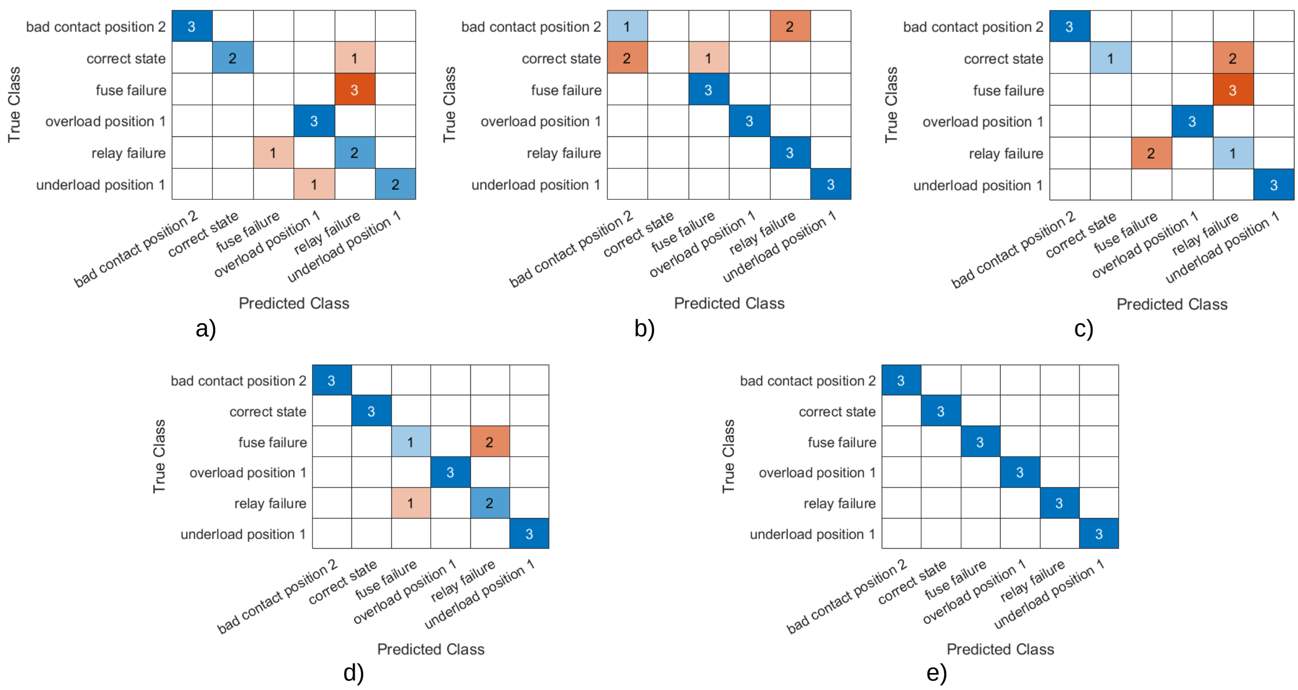

Fig. 11. *Confusion charts obtained with the implementation of different number of features in the KNN model: a) features 1 and 3, b) features 2 and 4, c) features 2 and 3, d) features 1, 2 and 3, and e) all features.*

4. Conclusions and Future Work

Progress has been made in the maintenance management of industrial equipment, machine or facilities, from applying corrective to preventive actions, until the current tendency of applying predictive maintenance, which tries to predict the failure of a component to be replaced or repaired before the failure occurs. Among the wide range of applications of infrared thermography, the maintenance is gradually spreading in the industrial sector due to its simplicity and effectiveness. Thermal data collected with a thermal sensor can be a very valuable source of information and can identify problems at an early stage.

The present study proposes to develop a predictive maintenance system based on the potential of infrared thermography technology, incorporating a set of functionalities and tools based on augmented reality, machine vision and machine learning to properly manage the maintenance activities. This manuscript describes the specific development of the classification model, based on the information extracted from the captured thermographic data and implemented to predict failures in industrial equipment.

Different industrial equipment has been considered to develop and validate the predictive failure model. Common faults have been induced to each of the equipment and its thermal characteristics have been extracted using statistical measures. It was found that a large number of the failures produced similar thermal behaviors, making it difficult to identify the specific type of fault by simple inspection.

The information obtained in the thermographic inspections was used to train a predictive system based on the KNN model. Different versions of the KNN model have been implemented using different number of features in the training stage. It was observed that the degree of accuracy in the predictions provided by the model increased when considering a higher number of thermal features, obtaining a total accuracy using all the selected features.

Future work will include the analysis of additional industrial equipment and other types of failure that may be of interest to maintenance companies. Additionally, other machine learning algorithms will be considered to predict failures and even the possibility of developing a system based on neural networks will be taken into account when the number of cases analyzed is sufficiently high. Finally, the automatic classification model will be integrated into the MANTRA predictive maintenance system.

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