Motor Overheating Monitoring Using Thermal Images And Artificial Neural Networks

1st Raoni Pontes
Polytechnic Institute of Coimbra - ISEC
Coimbra, Portugal
a21270977@alunos.isec.pt

2nd Mateus Mendes
Polytechnic Institute of Coimbra - ESTGOH and ISR - University of Coimbra
Coimbra, Portugal
mmendes@isr.uc.pt

3rd José Torres Farinha
Polytechnic Institute of Coimbra - ISEC
Coimbra, Portugal
tfarinha@isec.pt

4th Jorge Almeida
Polytechnic Institute of Coimbra - ISEC
Coimbra, Portugal
jalmeida@isec.pt

***Abstract*—Motor overheating is a serious problem, which can be caused by overload, poor maintenance, age degradation, among other reasons. If necessary precaution measures are not taken, it can result in premature damage of the motor or accidents. Monitoring the equipment condition, in this case the temperature, is a good way to prevent failures and enlarge its availability. The present paper describes the outline of a system to monitor running motors using a thermal camera. The camera takes images of the most sensitive parts of the motor in real time. The images are then processed, to extract the region where the temperature is higher. The region of the image at higher temperature is analysed. The area (as number of pixels) and shape of the region are then classified using an artificial neural network. The network is trained to recognize regions where the safety of the motor could be compromised.**

***Index Terms*—Motor Overheating, Thermal Image Processing, Artificial Neural Networks**

I. Introduction

When it comes to the use of infrared thermal imaging for automotive engines, there are only a few applications. In the area of Otto cycle motors, the use of infrared imaging has been used to detect variations in the temperature field in order to identify structural defects in the materials of casings, pipe lines, bearing housings and other engine parts. In that type of applications, infrared image evaluation is usually performed manually by a specialist.

The branch of engineering that is concerned with methods of assessing and detecting faults in materials and equipment without damage is called Non-Destructive Testing (NDT). Knowing that equipment integrity can be affected by possible failures, NDT is a powerful tool that can be used in Predictive Maintenance ensuring safe operation, quality control and equipment life assessment. Failures may be cracks, leaks or variations in structural properties that may lead to loss of strength or service failure. NDT has no clearly defined limits. It can be performed using simple techniques, such as visual surface examination. It can also be done using geometric and dimensional analysis, radiography, noise comparison and thermography. There are still other methods that require direct intervention on the equipment, such as vibration analysis, mean effective pressure, ultrasonic and airflow at the intake and exhaust systems.

Barelli et. all use an NDT methodology based on the characterization of working conditions through acoustic and vibration measurements and relates the data to the indicated mean effective pressure inside the cylinder [1]. Some indices are introduced in order to evaluate the engine working speed. The average indicated cycle, engine intake and exhaust valve lift level for different values of the produced electrical power are related to cylinder head vibration measurements and acoustic pressure levels in a close frequency range.

Sometimes some parameters are proposed in order to relate the data to the mean effective pressure indicated on the monitored cylinder, which indicates the operating state of the engine. Vibration measurement is a reliable methodology for assessing the quality of internal combustion engines, but requires the installation of sensors in the engine, which is not always feasible. Wavelet Packet Transform (WTP) is also a well-known way used for successful data and signal processing in condition monitoring and fault diagnosis. In this technique, the extraction of characteristics based on the transformation of wavelets is used, and the sound signals emitted by car engines are analyzed under fault and health conditions. The intention is to categorize the beeps into healthy and defective classes. Audible signals are generated from different car engines under healthy and faulty conditions. A problem with this technique is the noise generated by systems running parallel to the engine, which requires more arduous filtering work. Moreover, by the very nature of the signal generation at work, the detection of noise already represents a failure that is most likely linked to a considerable loss of efficiency [2].

The pressure signal on the cylinder can also be used to control the combustion engine cylinder filling process. The reason for this control is to optimize combustion in each cylinder in terms of performance, fuel consumption and emissions. The values obtained from the pressure signal are used to determine the descriptors directly involved in the control

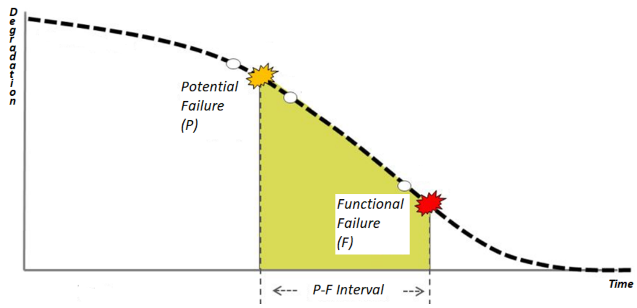


Fig. 1. P-F curve, illustrating the time between the probable occurrence of a failure and the actual failure.

process, such as the indicated mean pressure, the maximum pressure or the crank angle to which half a fuel dose was burned. To calculate the values of these parameters with appropriate uncertainty, complicated algorithms and thermodynamic models have to be developed along with the use of high processing power microcontrollers. Hence the need to look for easy fast methods of computing the combustion process descriptors: the beginning of the combustion angle or the angle corresponding to the maximum heat release rate. Some of the combustion parameters can be evaluated based on the mean value and standard deviation of the measured pressure in the cylinder [3]. Those estimates are easy to calculate, but are useful only when parameter values are distributed according to a Gaussian distribution. The literature review shows that the sign of mean pressure deviations is also easy to determine and has a significant information load. Another interesting point is the exhaust gas analysis, which has two main focuses, an exhaust gas analysis and an acoustic signal in the exhaust flow. The contents of the exhaust cannot be used to estimate the quality of the combustion, nor problems with the injectors and engine lubricants. Most exhaustion analysis are performed using a chemical analyzer score to record their component composition. In addition, exhaust flow monitoring with acoustics can also provide information on valve and injector problems, as well as other failures that affect combustion [4]. Although this technique has proven to be successful, it depends on intrusive exhaust flow measurement that is not feasible for industrial applications. The question of how viable it is in large engine applications due to the high exhaust temperatures that are in the region of 500 ° C immediately after leaving is also present, providing potential high costs for sensors and their continuous replacement.

Thermographic monitoring is a viable method, not only for its confirmed accuracy [5], but also for its ease of application for almost all desired monitoring conditions, whether static or dynamic situations.

The final objective is always the same: to enlarge the equipment's availability, namely through the P-F curve, as shown in Fig. 1 [6].

The present paper describes a model to develop a system that assesses the technical state and diagnoses possible anomalies of a gasoline engine during its operation based on infrared (IRT) images through an intelligent automatic system.

Section II describes the experimental setup. Section III describes the principles behind thermal images. Section IV describes the algorithm designed to process the images and obtain a classification. Section V draws some conclusions and future work.

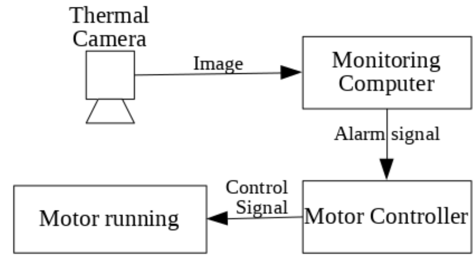


Fig. 2. Block diagram of the system.

II. Experimental Setup

Fig. 2 shows a block diagram of the system as it is planned. As the figure shows, the thermal camera is pointed to the motor. It is firmly positioned at a distance of the motor, so that it will not be affected by the motor vibrations or possible high temperatures that may be reached during operation of the motor. It is placed at a safe distance and pointing directly to the areas of the motor deemed more critical and, therefore, selected for monitoring.

The camera captures pictures in real time and sends them to the computer via a USB link. The computer receives the images and processes them at a sufficient frame rate. The frame rate is not yet determined, but considering the nature of the processes involved, a high frame rate is not necessary. That means a low power computer, such as a raspberry pi, is expected to suffice.

When a number of consecutive images is detected as corresponding to a pattern where the motor is overheating, the computer sends a signal to the motor controller, either to reduce speed or to halt. The frame rate (FR), the number of consecutive images that will raise an alarm (AL) and the actions to perform when an alarm is triggered will be defined in the next step of the project. The system is planned to be as general as possible. So those parameters (FR, AL and actions), will be left as variables of the model to be configured for each possible deployment of the system.

Image processing is done using OpenCV, in Python. Classification is done using Python Science Kit library SK-Learn.

III. Thermography Images

Thermal image, or thermograms, are captured by InfraRed (IR) cameras, which are sensitive to radiation in the range $9-14\ \mu m$. As all warm objects emit infrared radiation, thermal images give a good indication of the temperature of objects in the field of view of the camera. The higher the temperature of an object, the higher the amount of infrared radiation that it will emit and that will be measured by the thermal camera.

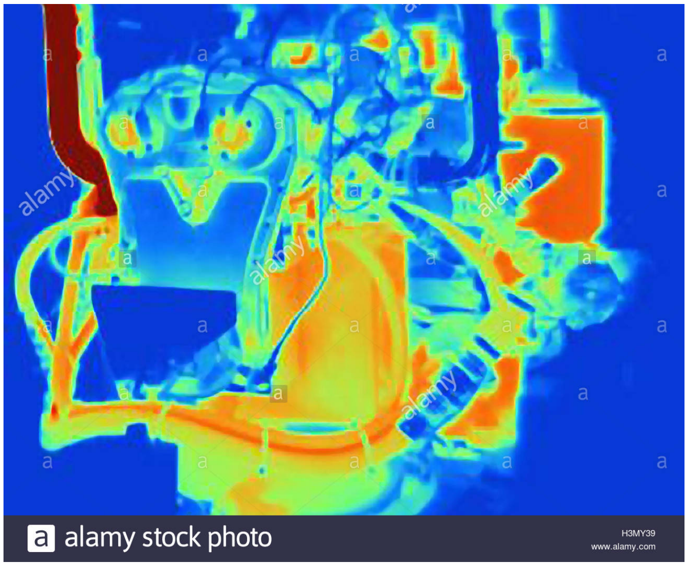


Fig. 3. Thermal image of a motor. Credits in the image.

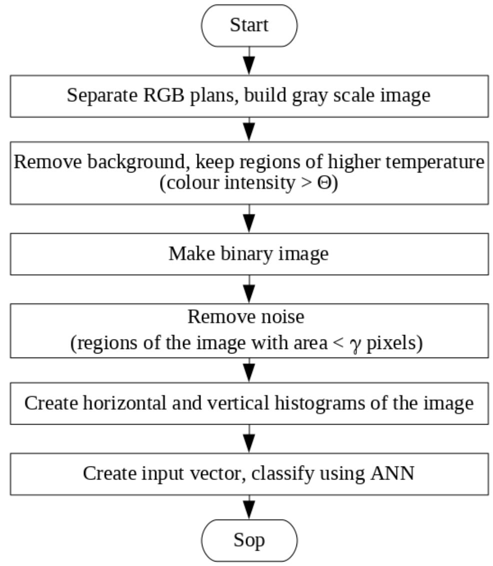


Fig. 4. Flow chart showing the main steps of the algorithm proposed for processing and classifying the images.

The camera will also capture radiant energy, which may be in the environment and pass through or be reflected by the object of study. Therefore, an adequate placement of the camera in its environment is required for best results.

IR radiation may be felt by humans as heat, but it is not visible. Thermal cameras, however, map the amount of IR radiation measured in a colour scale, in the range of colours visible to human beings. In many cameras the scale of colours may vary or may be adjustable. In general, however, dark colours correspond to the lowest amount of radiation and temperature. The the colour scale continues, from dark to blue, pink, red, orange, yellow and finally white.

Fig. 3 shows an example of a thermal image of a running motor. As the image shows, different areas of the motor are at different temperatures. The blue areas are at lower temperatures. That means the sorroundings of the motor are in general at low temperature. The exhaust pipe, at dark red, is at a temperature higher than the sorroundings but not too hot. The hottest parts of the motor are clearly at the center bottom of the image, where the colours are already a very light yellow.

The image of Fig. 3 is stored in RBG format, with 8-bit colour depth. That means it is composed of three colour planes, and in each plane the amount of colour for each pixel is specified as an 8-bit integer. The first plane plane specifies the amount of red, where a zero means no red in that pixel and 255 means the maximum amount of red in that pixel. The second plane specifies the amount of green and the last plane the amount of blue for each pixel. A black pixel will have zero in all planes. A white pixel will have 255 in all planes. The regions of higher temperature of the image will, therefore, have higher pixel values for all planes.

IV. Methods

Fig. 4 shows a flowchart outlining the main steps of the algorithm proposed to process and classify the images.

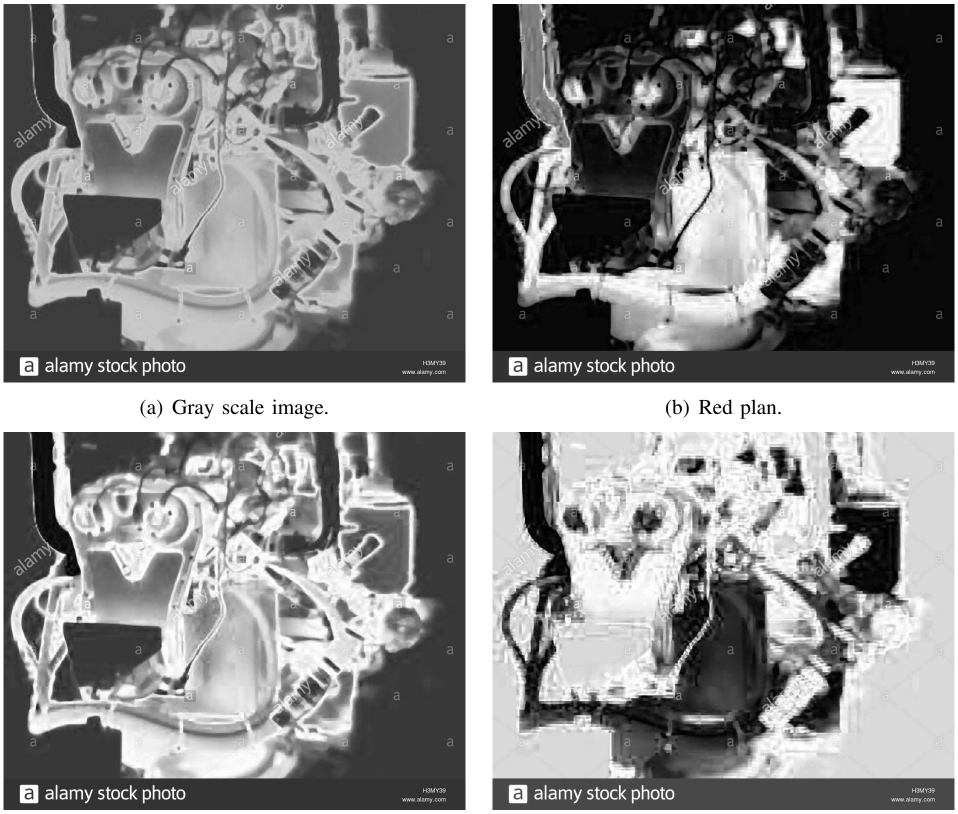
Once the thermal image is received, the first step is to get the separate RGB plans. Fig. 5 shows the different plans obtained for the image shown in Fig. 3. Each plan is shown in the form of a grayscale image, where black is represented as zero and pure white is represented as 255. From the separate plans it is possible to observe the contribution of each colour plan to form the RGB image. The amount of blue, as shown in Fig. 5(d), is higher in the cold areas of the picture. Therefore, the blue plan is a candidate to be ignored, thus reducing the amount of data to process without loss of information.

The amount of blue is also taken into account for the grayscale image shown in Fig. 5(a), which was generated using a common RGB to gray algorithm. So the grayscale image, formed using the common RGB to gray algorithm, is probably not a good candidate to be taken into account for further processing. A different method, where the image is generated decreasing the contribution of blue and increasing the contribution of the red and green plans, may be more adequate. The grayscale image of Fig. 5(a) was generated with OpenCV flag COLOR_RGB2GRAY, which uses Equation 1 applied to each pixel[1]

$$Y \rightarrow 0.299R + 0.587G + 0.114B \quad (1)$$

In the equation, Y is the value of a pixel in the grayscale image. R, G and B are the corresponding values of the pixel in the red, green and blue plans. The amount of blue taken for the grayscale image is already lower than the amount of

[1] According to OpenCV documentation, available at https://docs.opencv.org/3.2.0/de/d25/imgproc_color_conversions.html (last consulted 2019-08-26).



(a) Gray scale image.

(b) Red plan.

(c) Green plan.

(d) Blue plan.

Fig. 5. Different color plans of the image shown in Fig. 3.

green and red, but in the experiments it will probably be still decreased, in favour of the amount of red. So the image taken for further processing should be a grayscale combination of the red and green plans.

After the grayscale image is produced, it will be processed in order to remove the background and keep only the regions where temperature is higher. That means pixels with an intensity less than a threshold θ will be zeroed, therefore made black in the image. The pixels equal to the threshold and above are mapped to 255, so that the final image only contains two integer values. After this step, the image is only non-zero in the areas of higher temperature. However, it is expected to contain some noise, which can be seen in the form of very tiny spots in the image. Those spots are removed if they have area less than a threshold γ, which is a small number of pixels in the image.

After the previous steps, the image will contain only zeros, except for the regions of the motor which are hotter and have a certain dimension worth to analyse. Those areas may raise alarms if they are too big or have an unexpected shape. If their size is above a certain number of pixels, the system can immediately raise an alarm. Otherwise, the shape can be analysed using a neural network trained to recognize good and bad shapes.

The neural network planned is a feedforward model, with size to be determined experimentally. As input, it will have an image signature consisting of the horizontal and vertical histograms of the image. The histograms are created counting the non-zero pixels along the lines and columns of the image. Different hot areas will, therefore, create different histograms. The input to the neural network is therefore a vector with the format $x = [N_p, HH, VH]$, where N_P is the number of non-zero pixels in the image, HH is the horizontal histogram and VH is the vertical histogram.

V. Conclusion

Condition monitoring in motors is important to ensure their safety and extend operation time. The present paper outlines a project to develop a system to monitor a gasoline motor, using a thermal camera and artificial neural networks to classify the images and detect faulty patterns.

Future work includes experiments to determine the best type of images to feed the neural network, assembling the hardware and testing the method.

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