DEVELOPMENT OF AN IOT DEVICE USING MLX90640 SENSORS FOR TEMPERATURE ACQUISITION

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ABSTRACT: In this paper, a new IoT device is proposed for monitoring industrial processes. It has been developed in such a way that it is a low-cost device, uses temperature sensors and exposes the acquired data as thermal images, images that will be used as input data for prediction algorithms developed using convolutional neural networks.
KEYWORDS: IoT, predictive maintenance, temperature sensors, tool monitoring, thermal imaging.

1. INTRODUCTION

Predictive maintenance (PrM) [1] has recently been adopted by more and more industries and relies on the predictive capabilities of the operation of various systems to ensure adequate safety and reliability [2]. Recent developments in IoT (Internet of Things) technology, allow PrM systems to be developed to be efficient and cost-effective. This makes new PrM techniques to be adopted in industries where this was either not technically possible or not cost-effective [2]. PrM [3], [4] is an effective tool in reducing operating costs and frequency range for maintenance activities of industrial equipment [5], [6]. A significant part of the literature focuses on methods of acquiring sensor data and interpreting these data to identify potential problems in the fabrication process.

Specifically, from the point of view of interpretation of acquired data, in IoT-based PrM systems, machine learning models are used to evaluate acquired data and for decision making [7].

For the purpose of the above-mentioned considerations, the device proposed in this paper, is a low-cost device based on temperature sensors.

This device exposes the acquired data in a format optimized for its analysis using convolutional neural network (CNN) based algorithms [8]. These prediction algorithms were chosen because they can take a set of input data, assign importance to different aspects or features in the data, and distinguish between them. Such algorithms are used to determine the faults of some components of a manufacturing cell in order to monitor it in real time [9], [10], [11] and [12]. CNNs are also used for processing signals with a significant noise component [13].

2. IOT DEVICE ARHITECTURE

The proposed device was designed to capture the temperature of a milling tool within a manufacturing cell. The actual testing was performed in an experiment carried out with a milling tool used by the UO-01-FMC manufacturing cell [14], [15], [16], [17] in order to determine its wear degree.

In order to achieve the goal set in the experiment, it was decided to use convolutional neural networks for the development of the decision algorithm, and in order to achieve better and faster results in terms of training the models, it was decided that the device would generate thermal images based on the acquired temperature values. This decision was taken because CNN-based classification algorithms give particularly good results in image categorization.

As a conclusion, the IoT device was developed based on temperature sensors, and the acquired values were automatically converted into thermal images that could be further processed by decision algorithms.

The MLX90640 temperature sensor [18] was used for data acquisition, together with a Raspberry Pi 4. These were mounted using an adjustable holder made by 3D printing, as shown in Fig. 1.

Constructively, the device follows the block diagram in Fig. 2.

Figure 1. Mounting of the MLX90640 sensor

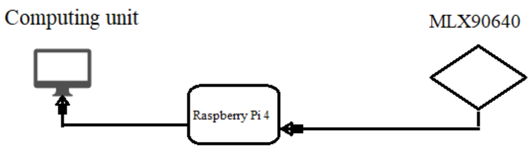

Figure 2. Block diagram of the IoT device using the MLX90640 sensor

The temperature acquisition accuracy is ±1.5 °C and allows acquisition from a distance of several metres. Communication is via the Qwiic system exclusively via I2C. This sensor provides a field of view of 110°x75° and allows the acquisition of temperature values between -40°C and 300°C.

The MLX90640 sensor [18] has an array of temperature sensors of size 24x32, each of which acquires a temperature value, and through processing using an algorithm written in Python these temperatures are transformed into images with a resolution of 32x24 pixels that can be further processed using specific classification algorithms.

The algorithm written in Python that transforms the temperature vectors into the corresponding images is the following:

```
import time
from datetime import datetime
from csv import writer

import busio
import board
import adafruit_mlx90640

from PIL import Image
i2c = busio.I2C( board.SCL, board.SDA )
time.sleep( 1 )
mlx = adafruit_mlx90640.MLX90640( i2c )
mlx.refresh_rate =
adafruit_mlx90640.RefreshRate.REFRESH_2_HZ
mlx_shape = ( 24, 32 )

def append_list_as_row( file_name,
list_of_elem ):
    with open( file_name, 'a+', newline =
'' ) as write_obj:
        csv_writer = writer( write_obj )
        csv_writer.writerow( list_of_elem
)

def rgb( minimum, maximum, value ):
      minimum, maximum = float( minimum ),
float( maximum )
      ratio = 2 * ( value-minimum ) / (
maximum - minimum )
      b = int( max( 0, 255 * ( 1 - ratio )
) )
      r = int( max( 0, 255 * ( ratio - 1 )
) )
      g = 255 - b - r
      return r, g, b

while True:
      try:
            mlx_image = Image.new( "RGBA",
( 32, 24 ), "black" )
            mlx_image_name =
datetime.utcnow().strftime(
"%Y%m%d%H%M%S%f" )[ : -3 ]
            mlx_list = [ 0 ] * ( 24 * 32 )
            mlx.getFrame( mlx_list ) #
read MLX temperatures
            row_counter = 0
            column_counter = 0
            for h in range( 24 ):
                  for w in range( 32 ):
                        temperature =
mlx_list[ h * 32 + w ]
                        r, g, b = rgb( 20,
40, temperature )

      mlx_image.putpixel((column_counter,
row_counter ), ( r, g, b ) )
                        column_counter +=
1
                  column_counter = 0
                  row_counter += 1
            mlx_image.save( "/home/pi/" +
mlx_image_name + ".png" )
            mlx_list.append(
mlx_image_name )
            append_list_as_row(
"/home/pi/values.csv", mlx_list )
            print( mlx_image_name )
            time.sleep( 1 )
      except ValueError:
            continue # if error, just read
again
```

One of the images generated based on the acquired temperatures is shown in Fig. 3.

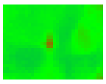

Figure 3. The image captured by the sensor

3. VALIDATION OF THE SENSOR ACQUIRED VALUES

Considering that the MLX90640 sensor is a low-cost one, we wanted to confirm the correctness of the acquired data. In order to confirm the data acquired from the MLX90640 sensor, the experimental stand also included a FLIR SC 640 thermal imaging camera [19] (Fig.4). The camera acquired images of the chipping process concurrently with the MLX90640 sensor, the difference being that the FLIR SC640 system took a video of the chipping process. The camera produced by FLIR is a professional camera dedicated to research. The main features of the thermal camera are 640 x480 pixel revolution, thermal sensitivity (NETD) <0.05°C, accuracy +/- 2% of reading, measuring range -40 to 2000°C, 8x continuous zoom with image rotation function, 24 degree/standard interchangeable lens; x2 super-angle x0.5 telephoto lens, thermal focusing: auto/manual.

Figure 4. FLIR SC 640 camera

Fig.5 shows the stand used for IR image acquisition and the positioning of the FLIR camera so that it captures the same images as the MLX90640 sensor.

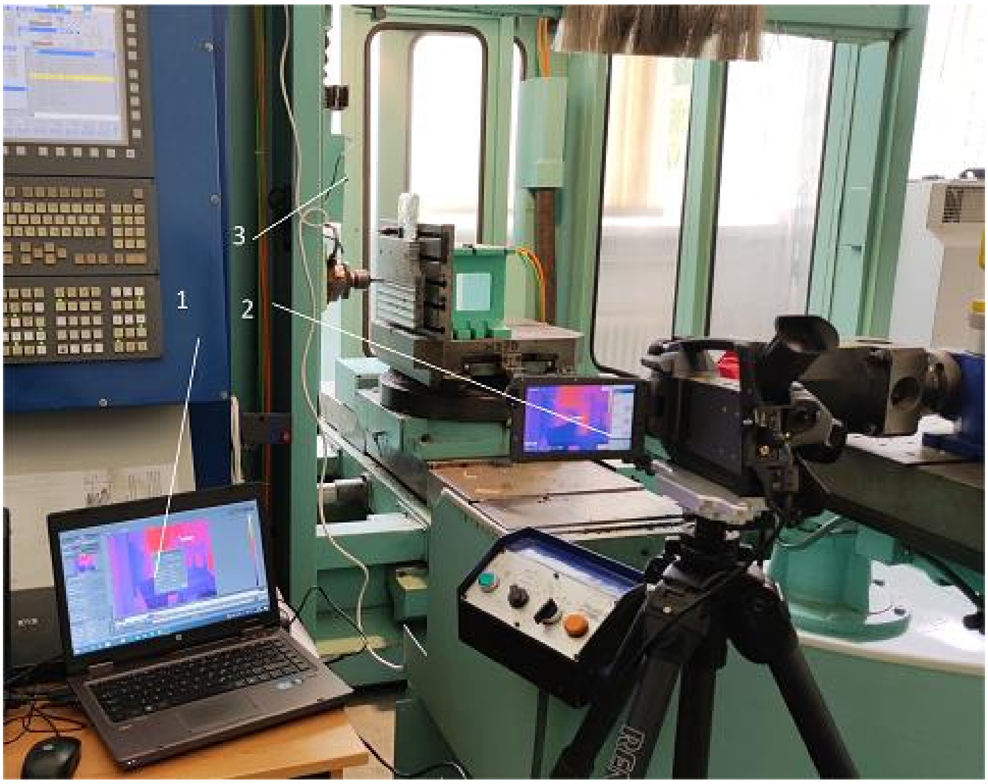

Figure 5. Image acquisition stand (1 computing unit, 2 FLIR SC640 cameras, 3- IoT device with MLX90640 sensor)

The arrangement of the equipment in the way shown in the figure is made possible by the optical image magnification capability of the FLIR camera, so that both acquisition systems have the tip of the image of the slicing tool in the centre of the image.

The Flir Reporter 9.1 application was used to process the IR images and obtain temperature information from the FLIR SC 640 camera (Fig. 6.).

The analysis found that the difference between the temperature values acquired using the MLX90640 sensor and the FLIR SC 640 thermal imaging camera respectively are within the accuracy range of the MLX90640 sensor, so the acquisition is compliant and thus the use of the IoT device using the MLX90640 temperature sensor is suitable for the purpose of the experiment.

Figure 6. Temperature information from the FLIR SC 640 camera

4. CONCLUSIONS

The low-cost IoT device developed based on the MLX90640 temperature sensor was developed and tested so that it can be integrated into a predictive maintenance system to determine the wear of the milling tool in a flexible manufacturing cell. In order to be sure that the acquired values were true to reality, they were compared with those acquired at the same time with a FLIR SC 640 thermal imaging camera and it was determined that the errors fell within the nominal error range mentioned in the data sheets. In addition, since it was decided to use prediction algorithms developed using convolutional neural networks, the IoT device was developed in such a way that the acquired temperature strings were converted into digital thermal images.

It can thus be concluded that the IoT device developed based on the MLX90640 temperature sensor that converts the acquired temperatures into digital thermal images is suitable for implementation in a PrM system designed to determine the degree of wear of a milling tool in a flexible manufacturing cell.

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