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Computer Vision based system for composition detection

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Abbreviations

Acronym	Description
AI	Artificial Intelligence
NIR	Near Infrared
MIR	Mid Infrared
PVC	Polyvinyl Chloride
RGB	Red, Green, Blue
ABS	Acrylonitrile Butadiene Styrene
PE	Polyethylene
PS	Polystyrene
PCA	Principal Component Analysis
JSON	JavaScript Object Notation
HDR	Image Format
FOV	Field of View
LIF	Laser-Induced Fluorescence
IoT	Internet of Things

1 Introduction

This report summarizes the work done up to the M12 by Canonical Robots and the design and implementation of technology within Pilot 1. In collaboration with Thermolympic and LOLO containers they aim to create a pilot plant or tool that allows the classification of plastics to be used both in the Thermolympic factory for processing the surpluses within its plant and the plastics gathered and processed by the LOLO recycler. The tool must identify the chemical characteristics of the processed material that allows classifying these residues according to their chemical composition, thus certifying the product processed with the tool. To start with , the work was dedicated to provide a solution to the Thermolympic problem, to classify automotive plastics that are difficult to recycle due to their physicochemical properties. Once this problem is solved, the classification of plastic available (gathered by LOLO or generated by Thermolympic) will take place according to the chemical properties of the materials, to be available for further requests.

1.1 Project Introduction

The overall vision of CIRCULOOS is to deliver the tools to enable MSMEs become full members of the Circular Manufacturing value chain. These tools orchestrate and continuously optimise the supply-chain end-to-end and integrate planning and execution monitoring to enable transparent and on-time communication. Combining these with direct calculation of the product sustainability and circularity profile, for both internal and external partners, this environment will enable them to configure and execute disruptive circular manufacturing processes for sustainable production that covers the entire life cycle of products; either by recovering the value of product that ended-up as waste or from recycled and remanufactured products.
To achieve this objective the project aims to deploy:

- Circular end-to-end supply chain orchestration for collaborative workflows which incorporates planning and execution metrics and integrates advanced and multimodal visualisation and analytics. The visualisation is delivered by comprehensive Digital Twins of the supply chains formulated, the factory processes and product design phases.
- Supply Chain Optimisation that monitors the global (across the supply chain) and local (within the factory) processes and execution, inputs and outputs and configuration parameters, to enable data-driven AI decision making, this way supporting continuous optimisation of targeted and measured performance and sustainability parameters.
- Dynamic Sustainability Assessment functionalities that investigate alternative supply-chain scenarios (varying in terms of materials used, processing technologies, suppliers involved and/or activated circular economy practices) in place of the existing schemes, quickly measuring their performance in terms of environmental sustainability and circular economy profile.
- Supply Chain Data Spaces for seamless, multi-level data flow across the supply chain partners, supporting the reuse of materials in novel products, the extension of the life-cycle of finished products (remanufacturing), and data-driven decisions for collaboration of parties offering matching services in the most dynamic and efficient way.
- Cybersecure and trustworthy data sharing across the supply chain by employing a distributed, trusted and efficient Identity and Access management system, that together with the associated trust framework will coordinate the identities of all IoT objects and ensure trustworthy data sharing among its members, aligned with the trust framework that is being implemented in EBSI.

- CM specific tools for the automatic recognition of recyclable parts by modern Machine Vision tools and Advanced Robotics, to enable optimised flows in the selection process.
- Novel circular business processes will be demonstrated supporting reusing, reducing, and recycling material in production and consumption systems. The new collaborative production models will provide quantifiable results on the sustainability increase across the supply chain, in terms of efficient use of raw materials, of by-products, of waste and energy and of emissions reduction. CIRCULOOS leverages the above with the RAMP integrated innovation IOT platform and the European network around it to deliver a CM ecosystem and platform for Manufacturing SMEs.
- Skills upskilling and reskilling will be provided in RAMP and through online courses, webinars, and best practice guides and success stories based on the pilots and Experiments for Demonstration (EXDs).

1.2 Tool description

In section 1.2, a brief description is made of the functionality of the tool created by Canonical Robots. Later, more details are given regarding the implementation, current status, research and steps followed.

Canonical is working on the design of a plastic recycling plant, focused on the classification of automotive plastics. Although it may sound as a solved or trivial problem, it is complex still and appropriate solutions do not exist.

Currently, most of the automotive plastic is discarded due to the difficulty in its classification. A characteristic such as the black color of the parts means that it cannot be separated with visual methods and, due to the similarity between different polymers, the rest of the separation methods are inefficient. Therefore, solving the problem of recycling this type of waste is a challenge for CIRCULOOS.

In addition to solving this problem, our plant will be integrated to the rest of the CIRCULOOS architecture in order to certify the waste that will be put into the CIRCULOOS surplus purchase-sale system in which the actors will be able to exchange the production surpluses by injecting this material again, promoting circularity.

This tool, enables to visually (digitally) capture the type of plastic for classification and to give the client guarantees regarding the type of material they are injecting into their production system.

This is the case of Thermolympic, this manufacturer requires car parts. These parts must pass strict quality standards required by their end customer. Injecting a low-quality plastic or plastic mixed with other components would result in not meeting Thermolympic's criteria of its customers requested quality, so guaranteeing the purity of the material is essential.

The tool proposed by Canonical is based on reflection spectroscopy. This technology or measurement procedure is based on reading the light returned by the material to be classified using optical sensors. By interpreting this reflected light we are able to differentiate one material from another. This process will be supported by a mechanical/robotized system to automatically separate the material from the rest in order to be classified.

2. Implementation approach

2.1 Theory

A short theoretical analysis took place to set the boundaries of the work and exploit the current state of the art.

The core of the work is the algorithm for plastic classification. The system takes information and process it and after that schedules an action, in this case picking the waste and classifying it.

The way in which the data must be collected is non-invasive, as data of the material is captured fast and at a distance, using light. There are three related measurement mechanisms, performing measurements by reflection, absorption or transmission.

Since the material travels through the conveyor belt, the measurement mechanism used for this purpose is reflection.

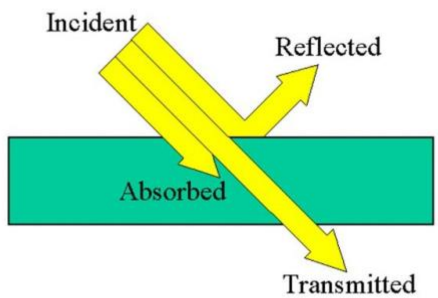


Figure 1 Schematic of measurement mechanisms

The amount of reflected light that arrives at one wavelength or another is very particular to each material. Therefore, by carrying out measurements at different wavelengths, a reflected light signature can be obtained, which is unique for each material.

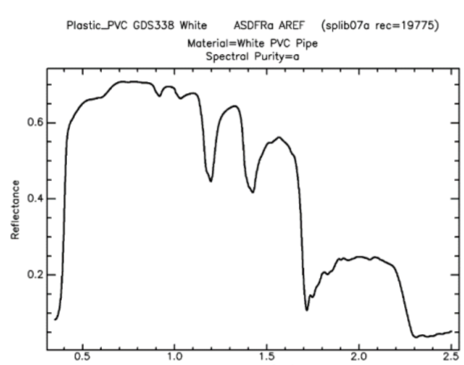


Figure 2 PVC Reflectance Spectrum

To measure reflected light at different wavelengths, a hyperspectral camera must be used. To understand how a hyperspectral camera works, a brief introduction must be made to explain how image acquisition works.

What hyperspectral cameras do is read pixel by pixel the wavelengths that that region of the material reflects. To understand it better, simplify the exercise with an **RGB image**. An image is the composition of three channels (wavelengths) labeled Red Green and Blue

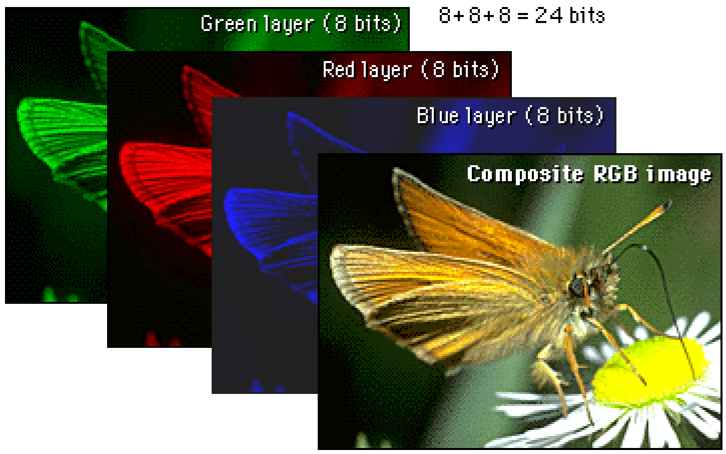


Figure 3 Composition of an RGB image

Now imagine that instead of evaluating three channels, you evaluate 200 channels, this would be evaluating 200 different "colors", in other words, you would be evaluating 200 different wavelengths.

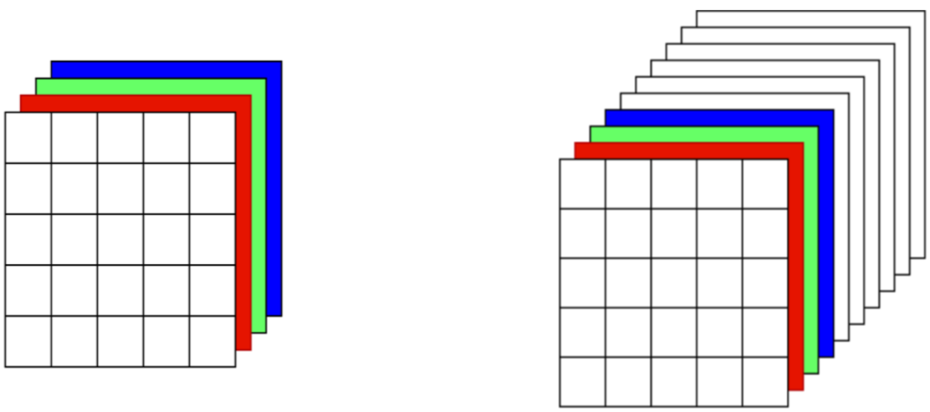


Figure 4 Comparison of the RGB image and hyperspectral image

The image on the left represents the channels that make up the image in RGB, that is, it represents the red, green, and blue channels that make up an image in the visible spectrum.

On the right a **HYPERSPECTRAL image** is shown, which is simply an image composed of many more channels which, since they are not visible with human eye.

Each layer represents the amount of light at a wavelength X (channel) that is read from a certain pixel.

By having so many layers and by representing them graphically it gives us the appearance of being a cube, and because it is so large, they give it the name HYPERCUBE. But they are only layers like RGB ones.

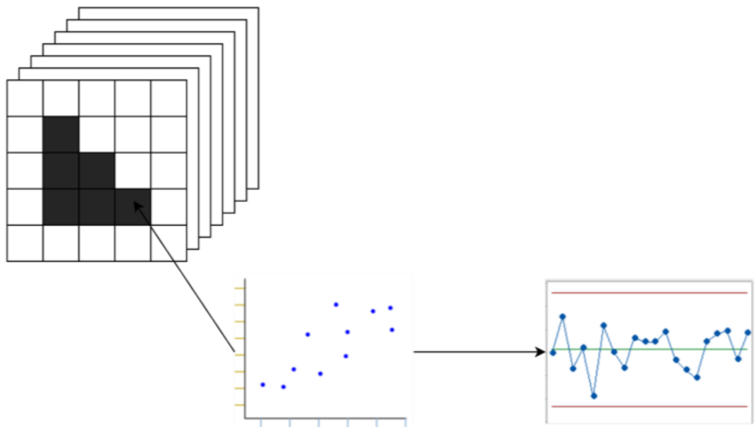


Figure 5 Composition of a hyperspectral image

The image with a resolution of 5x5, presents the layers of the channels in which readings are performed.

To see the spectral signature of the material, the levels of light that are reflected are taken and represented in a graph, joining all the points, it would give us a certain spectral signature as shown in the second graph. This spectral signature is unique to a type of material.

Another point to understand the following sections is to comprehend how the optics of a camera work. Usually, we work with linear cameras. A linear camera is a camera whose sensor has a linear form. That is to say, its pixel distribution is linear.

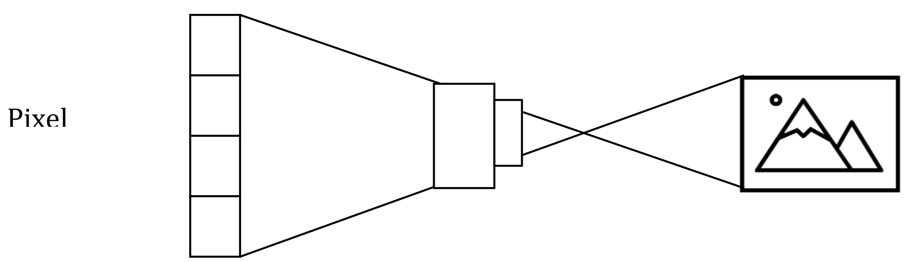


Figure 6 Object projection over a image sensor

Figure 7 Example of an objective in a lineal camera

The image is projected through the lens onto the pixel array. In the previous section, light and wavelength are discussed to facilitate an understanding of these concepts. Now, optics are used to comprehend the camera selection and the necessary setup. The camera will be positioned above the conveyor belt. There are several parameters to configure, including the camera height, conveyor width, conveyor speed, and the size of the objects.

For an object to be detected by the sensor, its projection must be the same size or larger than the size of the sensor pixel. We'll provide an example for better understanding. Imagine you want to measure an object with a ruler (the sensor) that is divided into intervals of 1 cm. Now, the object you want to measure has a size of 0.9 cm. Approximately, measurement can still be made, but with some error.

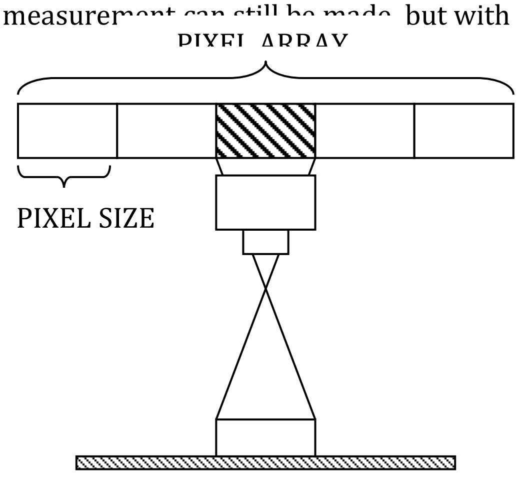


Figure 8 Image projection onto pixel array

The object should n't occupy more than one or two pixels so that but try with only one camera to occupy all the width of the conveyor belt. For this the number of pixels in 1mm on the conveyor belt should be defined. This way, the camera can see a certain object at a certain distance with sufficient resolution.

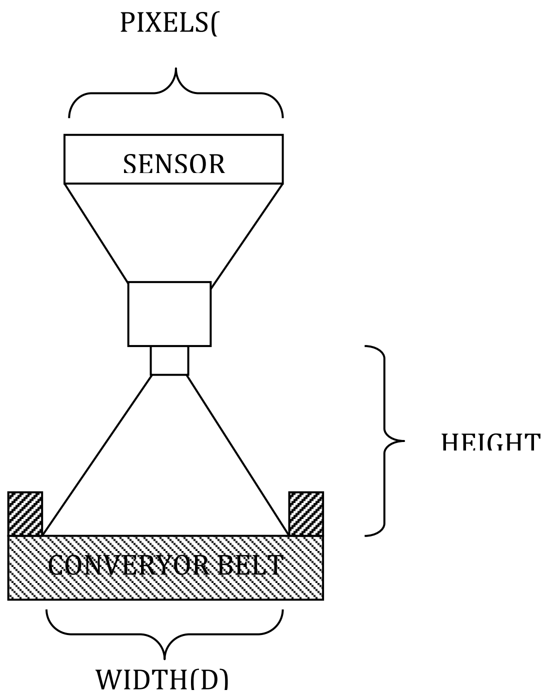


Figure 9 Small object projection over the sensor

$$R = \frac{D(mm)}{N(p_x)}$$

Equation 1 Relation between the conveyor width and the pixel resolution

R calculates how many millimeters on the tape correspond to one pixel of the sensor. For example, if the conveyor is 1000 mm wide, and the sensor has a 680 px resolution, the ratio is 1000mm /680px =1,47 mm/px.

$$R \approx 2\left(\frac{mm}{Px}\right)$$

Equation 2 Example results

It is noteworthy that 2 mm on the conveyor is equal to 1 pixel on the sensor. This leads to the conclusion that an object smaller than 2 mm occupies less than one pixel, making it undetectable by the camera.

Next is the determination of the position of the camera, for which trigonometry is used, knowing the width at the conveyor and the **FOV** of the camera.

The **FOV** of the camera is a parameter that this type of devices and is the opening in degrees.

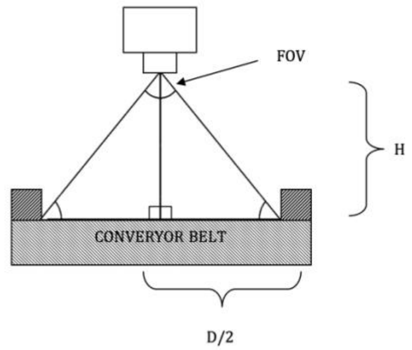


Figure 10 Trigonometry demonstration

$$H = \frac{D}{2 \cdot \mathrm{tg}\left(\frac{FOV}{2}\right)}$$

Equation 3 Equation for calculate the camera position.

This introduction about spectroscopy is the basis of the proposed system composed of a hyperspectral camera.

2.2 Researching

The solution was designed to be both economically, technically and commercially viable, considering expertise of technology providers (cameras, etc) and spectroscopy.

This journey is reflected in below sections where all the steps, conclusions and results obtained will be shown.

2.2.1 Stage 1

The analysis of the state of the art, proved that possible commercial solutions existed. In addition, research on visual inspection system and how it could be applied to sorting plastics took place. Following the understanding of how spectroscopy works and how information is obtained from the material, a market study was carried out to select the components needed for the first proof of concept and proved that a high TRL solution was not available at an affordable cost.

In this first step, a preselection of components was made for the study to capture the performance and precision. This first preselection is reflected in the attached table 1.

Hyperspectral cameras are high-precision devices that are expensive, and it is not common to be able to access this equipment temporarily by lending or renting.

Despite this fact, several devices were tested to conclude which ones best fit the requirements and thus be able to narrow down the problem.

2.1.1.1 Test 1

After evaluating the different alternatives in hyperspectral cameras the first test with the BLACK INDUSTRY SWIR 1.7 MAX took place. Although all the alternatives investigated cover the same wavelength, this parameter was not considered a differentiating factor. Another aspect evaluated was the frame rate, which although it varies between the options, did not turn out to be relevant since all the cameras operate at a sufficiently high speed. The FOV (field of view) was also tested, but since these cameras have interchangeable lenses, the manufacturers offer more than enough options to configure the FOV, which makes it a non-crucial parameter in the selection.

The choice of this camera for the first test was influenced by three main factors:

A: the minimum object size it can detect, which is essential for classifying objects with our prototype.

Figure 10 BLACK INDUSTRY SWIR 1.7 MAX

Figure 11 HAIP brand hyperspectral camera

B: its ability to detect the smallest objects. C. the price, although it is not the cheapest option, it offers the possibility of testing the camera before making the purchase. D. its convenient feature: the possibility of programming it using high-level languages such as Python. E. the libraries, datasheets and other technical information that makes it easy to use.

The manufacturer sent the device to CAN laboratories where a small processing plant with a structure, a conveyor belt, lights, device controls, etc was implemented.

The elements that compose the plant cell, are presented below with emphasis on required lighting.

A bad selection of lighting can give errors in the measurement. Therefore, a source that emits in a huge range wavelength was selected. A source sends light that hits the object and part of the light is absorbed by the material, and the remaining part travels through the material and other part is reflected. The wavelengths that are reflected are same that the emitted the source but a different power distribution.

For example, if the source doesn't emit in in range of the 1200 to 1400 nm the camera does not detect in this range. Because of this, it's necessary that the source emits in a great wavelength range because if it is less than the range of the camera, the camera is underutilized.

The ideal source for this application is the sun because it emit in all wavelengths with a similar power in all waves. It can see in the follow absorption graphic that the sun wavelength in different objects produces a continuous spectrum.

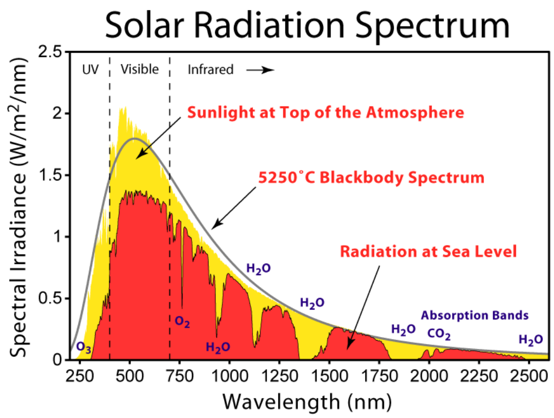


Figure 11 Radiation graph

The selection of a source that has similar characteristics, that is for this application, emits in the near infrared, is used, as the source emits in the near-infrared. In addition, the source should guarantee the continuity of the spectrum, not sources emitting in near-infrared ensure continuous spectrum. Fig 12 presents a comparative graphic which compares different light sources.

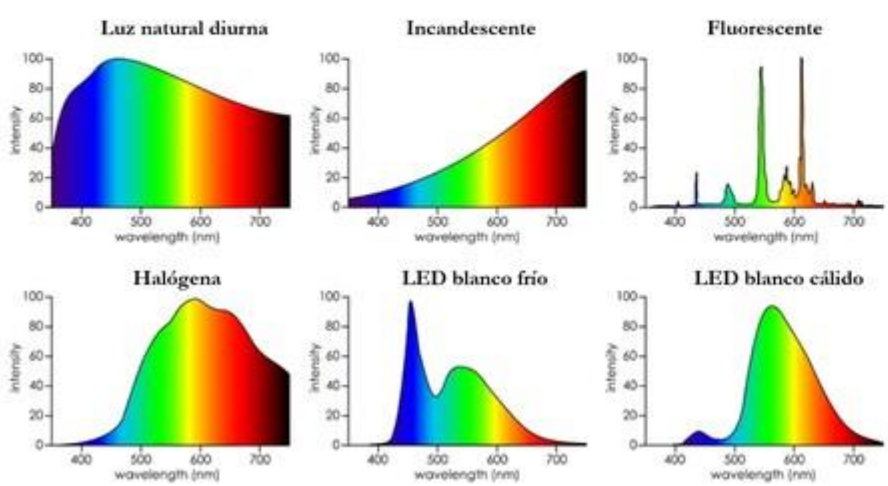
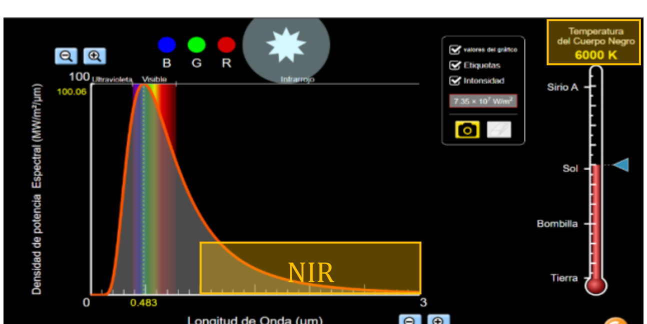


Figure 12 Comparison of light spectra depending on the type of source

The below graphic compares the thermal radiation as a function of temperature.



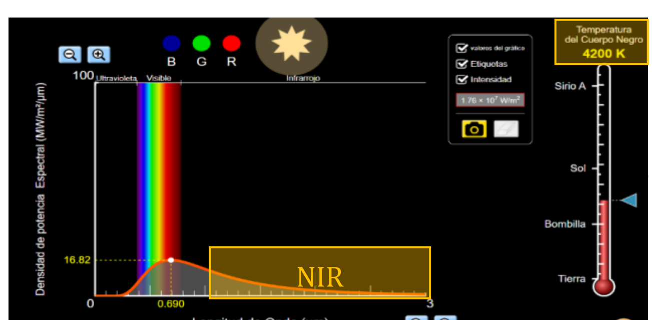


Figure 13 Graph of thermal radiation as a function of temperature.

Fig 13, shows that the temperature shifts the graph on the Y axis, but it is needed to search the maximum spectral power density(W/m^2). To achieve the goal to have a high NIR component and a continuous spectrum halogen sources are used. This kind of sources emit hot with continuous spectrum and provide the most value for money. Other kind of sources, were tested, such as LED sources. LED is a type of source very efficient; all energy is emitted in light form and are relevant for the spectrometry application but do not provide value for money. If the goal is to illuminate the LED technology this can be enough, but for this application the more interesting is that the source detach heat for a high NIR component.

Finally, the position of the devices selected should be more effectively designed. The position was selected for minimize the shades and thus be able to obtain a better spectral image and minimize errors.

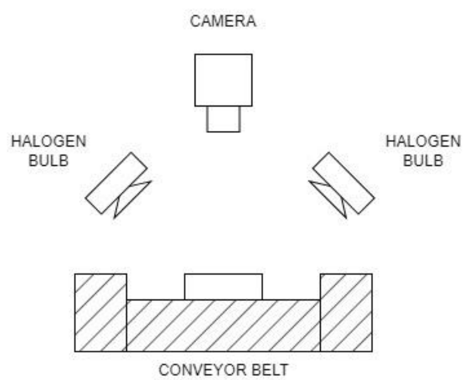


Figure 14 Arrangement of the chamber and halogens relative to the conveyor belt

After this specifications, the plant cell for the first test was set up.

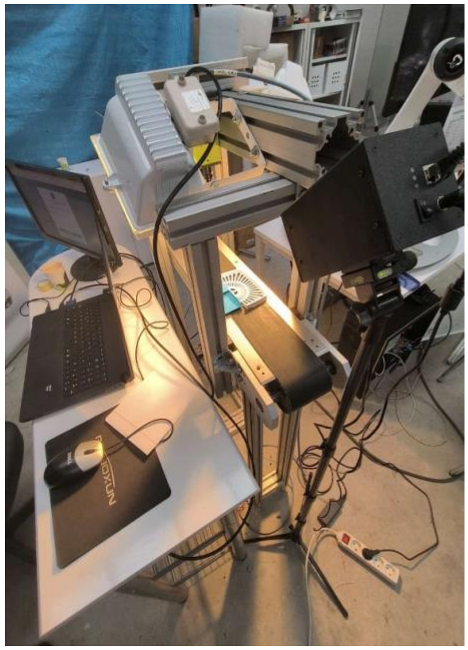


Figure 15 Assembly in Canonical's laboratory

When carrying out this first test, the results were not conclusive since the NIR band was very narrow, obtaining the reading of barely 200nm, which did not give a clear reading, giving the readings of the colored plastics the same pattern, which did not allow to distinguish one plastic from another.

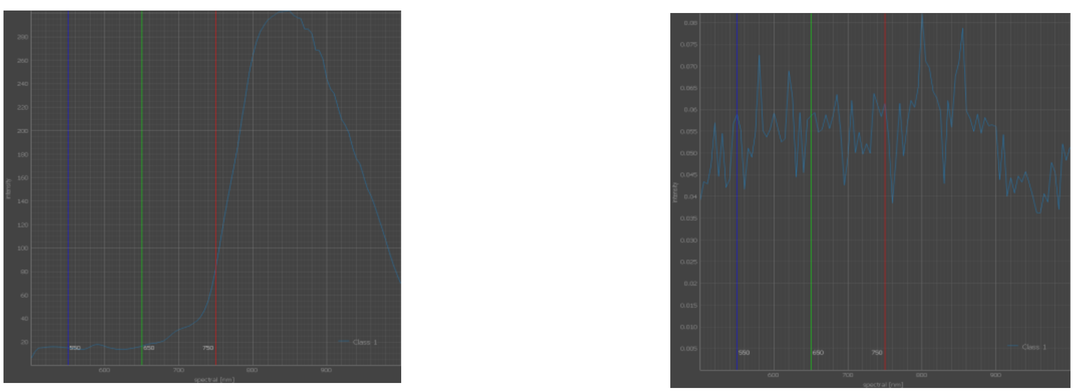


Figure 16 Results of the first study

CONCLUSION: The above results show that measurement range that should be expanded to draw relevant patterns within the measurements. Also the averages obtained with the black plastic were null since the graphs showed noise and therefore, inappropriate measurement.

2.1.1.2 Test 2

In this second test, the measurement range was modified to reach an interval between 900 and 1700nm. This second test was carried out with the EVK HELIOS EC32 camera and the following setup.

Figure 17 Equipment used by ClearView for testing

This test had to be carried out in the manufacturer's laboratories since there was no possibility of lending the device.

This test provided better results since the range was expanded and information was obtained that allowed a pattern to be found within the spectral averages. However, difficulties were again encountered when obtaining information on the black plastics. Two graphs below, compare the different PPs of different colors to demonstrate that the color pigments used in each plastic do not modify the measurement pattern. The second graph represents the measurements of one of the black plastics together with a colored plastic of the same type. In both graphs, the most characteristic areas of each spectrum are highlighted in red and allow us to identify each sample.

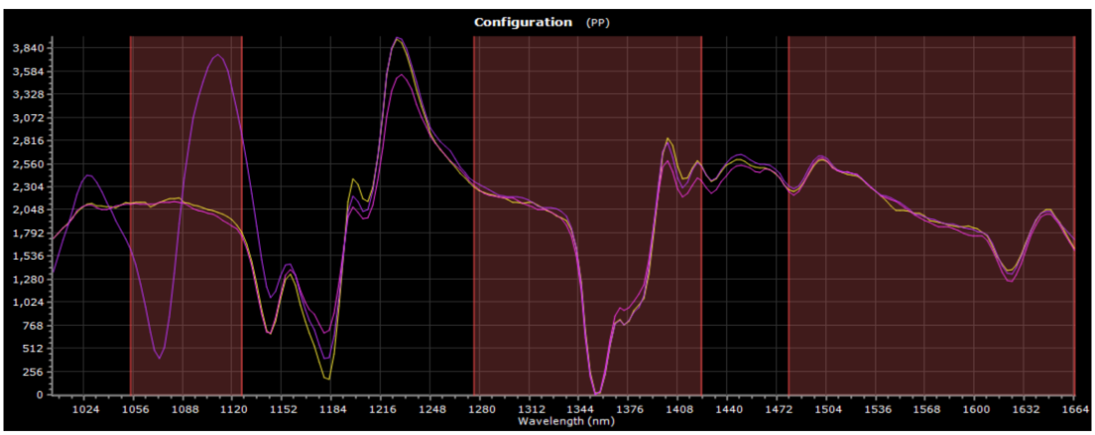


Figure 18 Spectral signature of PP plastics with color other than black

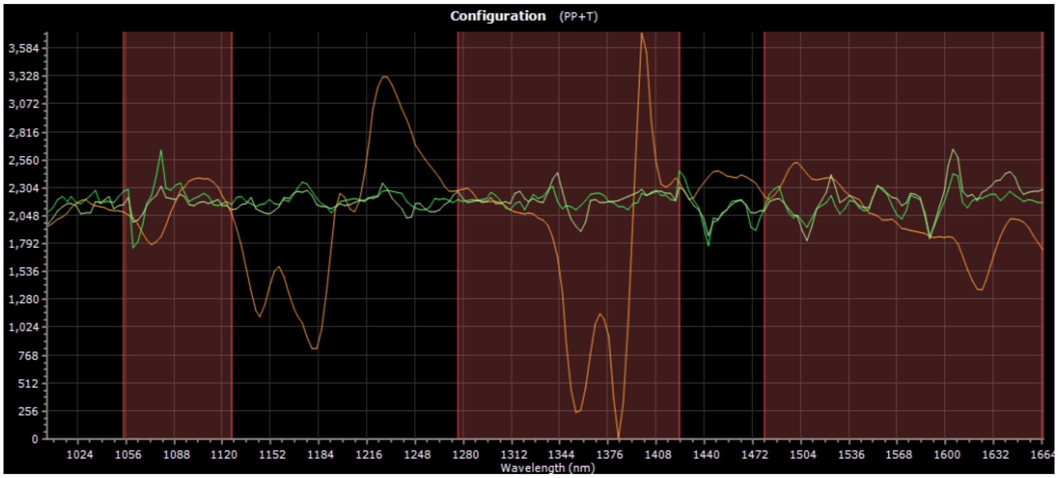


Figure 19 Spectral signature of PP+Talc plastic with a color other than black versus the same material in black

CONCLUSION: This second test showed that the color pigment used to tint the plastics does not affect the measurement, appropriate for classifying by family of plastics regardless of the color. However, black plastics continue to give inconclusive measurements because the signal read by the optical sensor is so low that it is very sensitive to noise. Therefore, further research is needed.

2.1.1.3 Test 3

The tests carried out with the SPECIM FX17 have been performed in the wavelength range between 900 and 1700 nm. Colours in plastics are achieved by adding pigments that could change the spectral signature, the "carbon black" pigment is used in the automotive industry to give black colour to parts, in this case the chemical composition of the pigment affect the measurements.

As shown below in the graph, the measurements are flat, that is and do not provide relevant information.

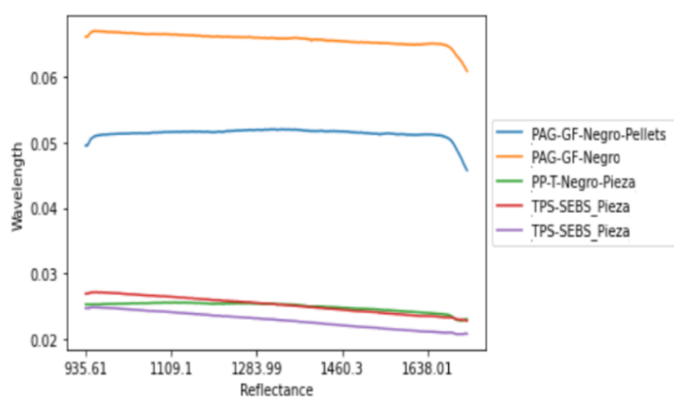


Figure 20 Comparison of the spectral signature of black plastics using the SPECIM FX17 camera

Carbon black absorbs visible and near-infrared (NIR) light, so it is necessary to move away from it to obtain information about plastics. It is proposed to use the mid-infrared (MIR) of approximately 2000 to 4000 nm.In the case of PP and PP+T plastics, they show similar spectral signatures with small variations due to color but which do not affect the measurement.

However, there is one of the measurements that stands out the most, and it is the one highlighted with the yellow circle.

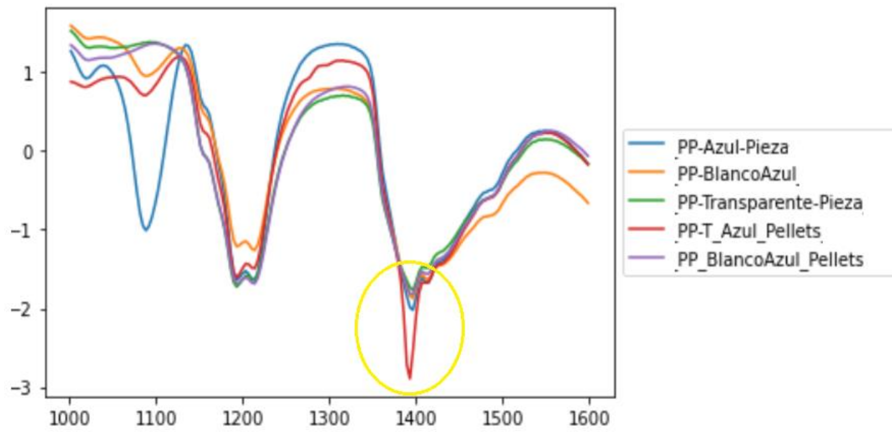


Figure 21Comparison of the spectral signature of color plastics using the SPECIM FX17 camera

Talc-containing plastics show an absorption peak of around 1400 nm. The absorption peak of talc coincides with the absorption peak of talc-containing plastic reading, so this would be a differentiating feature for sorting talc-containing and talc-free plastics

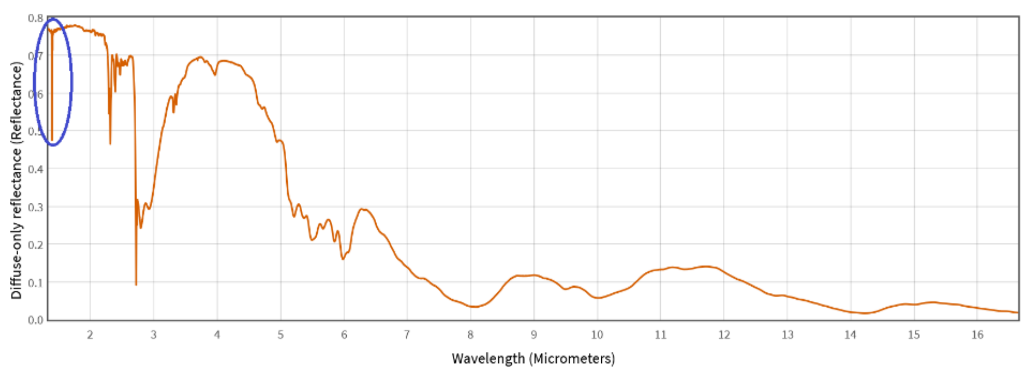


Figure 22 Absorption spectrum of talc with the absorption peak at 1400nm highlighted

CONCLUSION: This test refuted the good results of the previous test, in addition to detecting the problem of black plastics again.

Therefore, alternatives in terms of the mechanism or bands to be measured were still needed to detect black plastic. This is because black plastic has the black carbon pigment. This pigment absorbs all the light emitted in the visible range and in the near infrared. At the meeting in Zaragoza a database with many spectral measurements was provided captured by ED testing. The problem remains that not all measurements are valid because there are many mechanisms to add information to the spectrum of the materials, eg. Raman spectroscopy, diffuse spectroscopy, reflection, transmission or emission spectroscopy, etc.

LIF (Characterization and Discrimination of Plastic Materials Using Laser-Induced Fluorescence)

LIF (Laser Induced Fluorescence) technology, excites the functional organic bonds of the material we are processing, and based on the article called "Characterization and Discrimination of Plastic Materials Using Laser Induced Fluorescence" it became clear that some materials have the property of emitting light if they are excited with a certain light source. This method of exciting materials with light is called laser-induced fluorescence. Some materials have a valence layer and a conduction layer. Materials with full valence layer and an empty conduction layer, if irradiated with a light source, the electrons jump between the valence layer and the conduction layer. This jump is due to the electrons taking the energy from the light and jumping to the more energetic layer. Depending on the material, different reactions are noted, at a wavelength different from that of the light source.

The excitation depends on the energy used for excitation and the wavelength of the light. In fluorescence, the wavelength emitted by the material after excitation is longer than the wavelength used for excitation. This is because the energy is inversely proportional to the size of the wavelength. For example, ultraviolet rays are more energetic than infrared rays and the wavelength of ultraviolet rays is shorter than that of infrared rays. Taking advantage of this property for a beam with a light source with a shorter wavelength than that of the sensor (hyperspectral camera) used for detection may give the solution. However, it is still difficult to define at what wavelength the functional groups are excited or if this behavior is repeated in all compounds. For example, polypropylene is composed of a methyl group, a carbon double bond and an ester group. These bonds interact in a certain way with light if the beam has a specific energy and frequency. Researching through the internet[1], the mechanism to solve the problem is explained originating from fluorescence spectroscopy. Fluorescence spectroscopy uses light to excite the bond between light. It is the same as laser-induced fluorescence.

This paper showed that laser-induced fluorescence is a useful tool to characterize commercial plastic materials and distinguish between them and between plastics and other classes of compounds. The most significant spectral components in the LIF spectra collected for various plastic samples individualized by PCA. These wavelengths have been used to construct meaningful fluorescence intensity ratios that are used to automatically discriminate plastics and complex organic materials such as wood. Furthermore, a clustering algorithm has been applied to test the discrimination functionality of these ratios. An available alternative to solve the problem, which requires further research and work.

NIR (A discrimination model in waste plastics sorting using NIR hyperspectral imaging system)

The paper presents an interesting application because it uses a similar setup and similar algorithms to do the sorting of plastic, but it doesn't use black plastic because the reflectance signal is very low for measurements. This paper serves to know that our first step was good, but it does not solve the problem of black plastic.

MIR (Robust plastic waste classification using wavelet transform multi-resolution analysis and convolutional neural networks)

This study, focuses on 5 commercially available plastic materials that are commonly found in mixed plastic waste (MPW): black polystyrene (PS), black polyethylene (PE), dark blue polypropylene (PP), white polyvinyl chloride (PVC) and black polycarbonate (PC). These plastic samples were 1 mm thick sheets.

This experiment demonstrated that mid-infrared is useful for detecting these plastics. Therefore, a good way to continue the pilot is to focus the work on this range.

The problem here is that they performed the experiment in a laboratory with individual samples and not in an industrial environment. To repeat this experiment applying the mechanism in an industrial environment it is necessary to use other types of sensors.

To make measurements in the MIR, hyperspectral camera that works in this range of the spectrum, is needed however, reading in these wavelengths at an industrial level requires an high extra cost.

[1] https://www.keyence.com.mx/ss/products/marking/lasermarker/knowledge/principle.jsp

Multispectral Mid-Infrared Camera System for Accurate Stand-Off Temperature and Column Density Measurements on Flames

Mid-infrared multispectral camera system is proposed for accurate measurements of separation temperature and column density in flames In this article, researchers talk about flame characteristics using spectroscopy, and seek to obtain them using spectroscopic technology, seeking to improve the combustion process using the information obtained with spectroscopic measurements.

This article is interesting for the CIRCULOOS because of measuring pollution that is composed of carbon byproducts. Carbon is a compound giving problems because it absorbs all the light and which composes the pigment that Thermolympic uses in its plastics. Also, another problem that we are investigating is that the devices that to use are very expensive to implement in an industrial process.

It demonstrated that it is possible to obtain good results with a multispectral camera and reduce the cost of implementation. A comparison of measurements that apply hyperspectral techniques and multispectral techniques was provided. The graph below shows a flame measurement with a hyperspectral camera and the graph on the right shows a flame measurement using a 6-channel multispectral camera. For the hyperspectral measurements the Telops FIRST-MW camera was used and for the multispectral measurements a Thermosensorik SME 640. The experiment attempts to obtain the temperature and density of the plume using spectral measurements. Depending on the physical characteristic to be measured, the accuracy is higher or lower. This is relevant information to take measurements in the MIR and contact with a research group that aligns with our needs.

2.1.1.4 Test 4

In our fourth experiment, the focus was to measur spectra in the mid-infrared (MIR), a range that has proven to be sensitive enough to provide relevant information for sorting black waste. To optimize measurements, the camera SPECIM FX50 was used, known for its high performance and ability to make accurate measurements in the MIR spectrum. Given the high cost and technical complexities associated with operating this camera, preliminary testing to evaluate its performance presented a challenge. A lab provided by SPECIM allowed our tests with black plastics, to indirectly evaluate the capabilities of the camera. Since the tests carried out by SPECIM were carried out with ABS PE and PS.

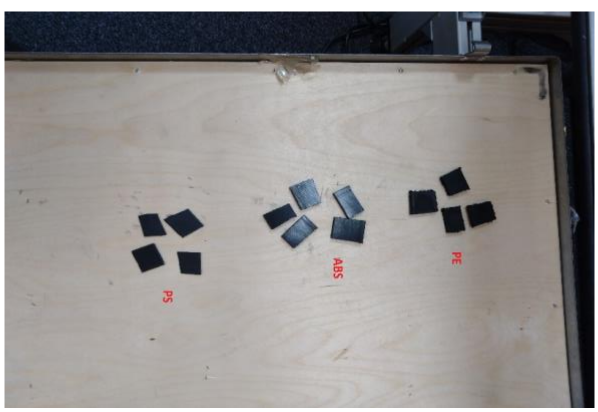


Figure 23 Black plastics used for testing PE, ABS and PS plastics in SPECIM laboratories with the FX50 camera

In the image above, the samples of the plastics used for this experiment are attached. In addition to these images, the HDR and DAT files visualized the data of the readings. This type of format is an image that stores the information of the spectra obtained by the sensor in each pixel. This means that when making readings outside the visible spectrum, their visualization, processing and analysis, involves the use of tools such as MATLAB or Python image processing libraries such as OpenCV or Spectral. After making the script for the management and opening of the data provided by SPECIM, we obtained the following graphs of the spectra of the different plastics.

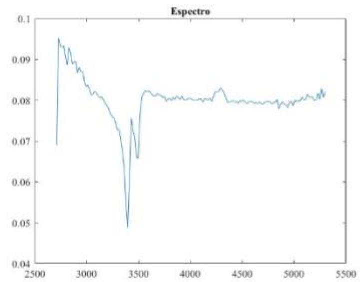
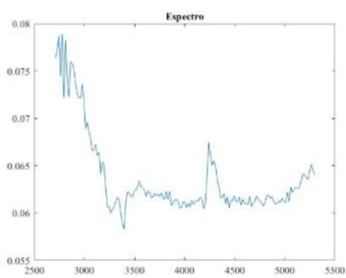
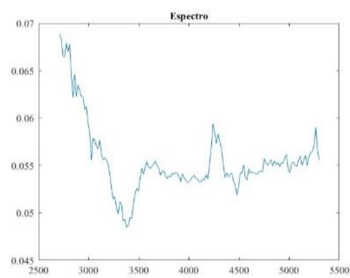


Figure 24 Spectra obtained with the FX50 camera

In the upper graphs the readings made with the FX50 camera are shown, starting from left to right the readings of ABS, PE and PS are attached. The spectra are totally different and allowed to discern between one plastic or another by reading their spectral signatures. However, looking at the scale and comparing it with the reading of the spectrum, for example of the background, which is made of wood, the signal is very low and still proves potential issues in readings due to the light returned from the plastic or simply noise in the light signal. This will still be further clarified in the next period.





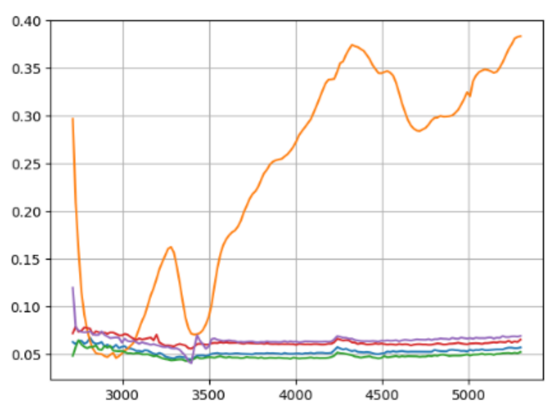


Figure 25 Reading the background with the orange graphic And the reading of the black plastics

2.1.1.4 Test 4

In the search for the device for the detection of black plastics, the collaboration of the Carlos III University of Madrid was sought, especially with the research group focused on the detection of components with this type of cameras. They also have a line of research focused on the detection of black plastics. A test is currently set up for the plastics processed by Thermolympicto help carry out a study under our criteria and conditions since we have full access to these facilities.

The setup used for the test was the following:

Figure 26 Assembly of the set up used in the laboratories of the Carlos III University of Madrid

Highlighted in red are the elements involved in the test. Element 1 is the Hyperspectral Camera, 2 is a blackbody, this device has a behavior similar to that of a light source, however it only emits infrared radiation, that is, heat. With this thermal radiation the samples are "illuminated" and marked on circumference 3.

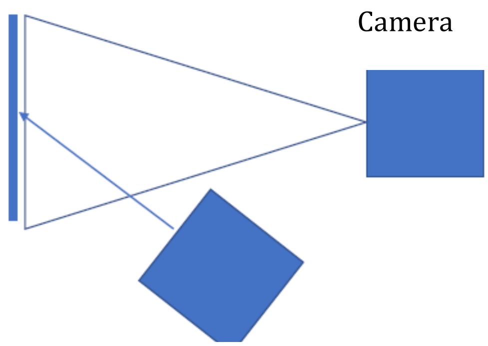


Figure 27 Layout of components

This type of camera must be cooled with water so the tests must be done on vertical targets. To do this, 4 test specimens were placed in which the different samples were glued on a surface that allowed the samples to be placed vertically.

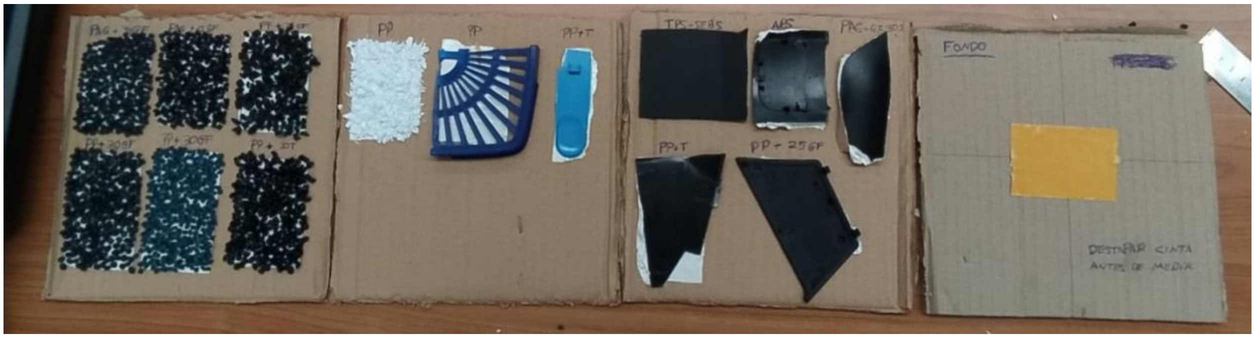


Figure 28 Samples of the plastics provided by Thermolympic adhered to a surface

These specimens were fixed on a support that always allowed a fixed position during the experiment.

Figure 29 Support for measuring plastic samples

The objective of this experiment was to see in which regions of the spectrum, the plastics processed by Thermolympic are more reactive to infrared radiation. Furthermore, the experiment sought to evaluate the viability of the project before experts who would test and evaluate the problem we were facing.

In addition relevant information about processing algorithms was given and ways to interpret the results and other relevant information from a reliable source such as a group of doctors. As a result of the experiment we obtained the following measurements:

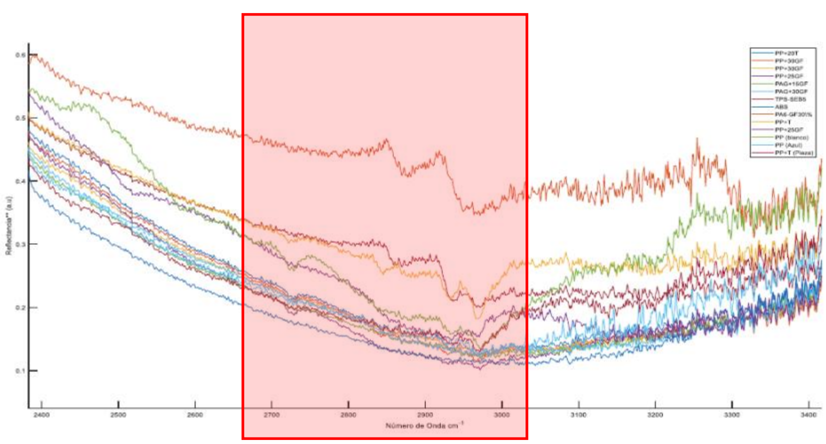


Figure 30 Results obtained from the plastics measured at the Carlos III University of Madrid

According to the experts' criteria, the region where it would be very possible to discern one plastic from another is in the region of the graph highlighted in red, where the most obvious differences between one plastic or another can be seen. differences that an algorithm could learn to differentiate.

They also proposed processing the data with PCA principal component analysis algorithms, which would allow reducing the dimensionality of the problem by obtaining only the most relevant data for classification. ***In conclusion of this last test and after the meeting with the experts who performed the test, it is not necessary to read all the bands since processing this information computationally is very heavy, in addition to not obtaining extra information, that is, reading more bands does not provide more information. Therefore, research and development will focus on searching for n bands within the region of the spectrum highlighted in red and looking for a Multispectral camera that reads in those chosen bands in order to try to make the project economically viable.***

2.3 Algorithm

2.3.1 Algorithm introduction

Regardless of the camera or setup chosen, the algorithm is the same. THyperspectral cameras are a type of camera which gives a matrix of values whose resolution is equal to the resolution of the format that the camera has configured by default, for example 600x 720 pixels, in case of working with color images the image obtained by the camera would be a matrix of 600x 720 x 3, that is, to represent the image 3 matrices or channels that represent the primary colors, are needed. However, the advantage of working with hyperspectral cameras is that they capture more "colors" and at wavelengths that the human eye cannot perceive. This gives us very valuable information when classifying materials.

If a hyperspectral image is broken down great resemblance to an RGB image is found, however if its information is represented it not only has 3 channels or matrices but has many more. Providers work with

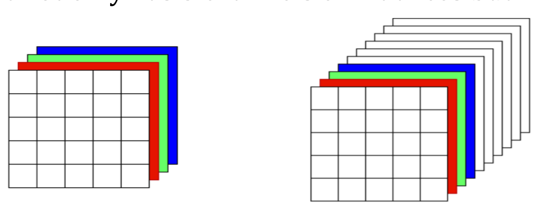


Figure 31 Comparison between the number of channels of an RGB image and a Hyperimage

up to 160 channels, this means that each pixel contains a vector of values whose size is 160.

So the information from a pixel gives a vector that represents the dimensionless values of the spectrum in that pixel, as see below showing, the reading of the spectrum value of a pixel within an ABS sample.

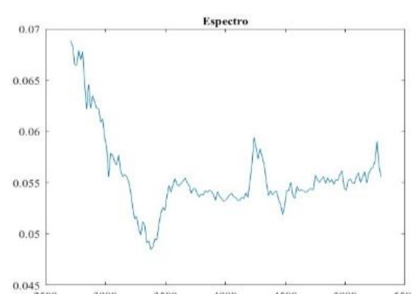


Figure 32 Spectral signature

At first glance a human cannot distinguish one plastic from another, however there are currently different algorithms that from many data and through iteration are able to reach an expected result.

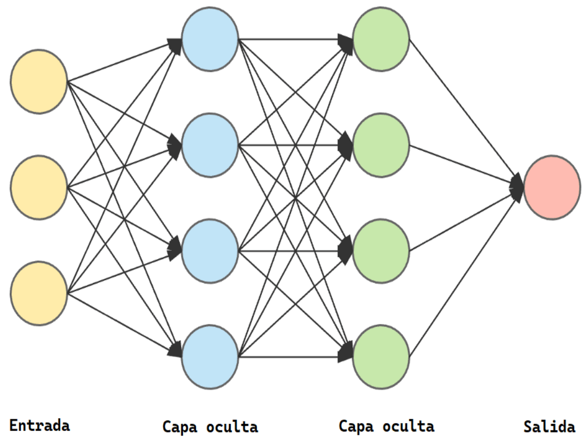


Figure 33 Neural network example diagram

Neural networks, are mathematical algorithms that process a large volume of data, resulting in data at its output which, interpreted in the correct way, can be used to process a large volume of data. information.

In the image above the concept of neural networks is represented, in which input neurons represent the input data, in this case there will be as many neurons as measured wavelengths (160), inside the network hidden neurons interconnected in one way or another depending on the type of data and the calculation to be performed and whose value is equal to that of the previous layer weighted by a weight.

The output layer, has as many neurons as the result needed. This type of algorithm is relatively new and the architecture and way of constructing it depends on the experience of the programmer.

2.3.2 Algorithm 1

In general view, an input layer equal to the number of bands read is planned, two hidden layers of type Dense. This type of layer connects all the neurons with all the neurons of the previous layer. It is a very powerful architecture since good predictive results are obtained, but its computational cost is very high, so it is only used for small data volumes such as case of CIRCULOOS.

The output layer initially is limited to 3 types, allowing to expand to more types in the future since the architecture and training are relatively quick to reconfigure.

The output will give three values between 0 and 1 representing the network's prediction for one plastic or another. For example, if we put a sample It will tell us that the type of plastic is ABS since the network has weighted ABS more in its output.

In a very general way, the way in which one plastic is going to be differentiated from another has been explained. Behind this brief explanation there is a strong theoretical component and programming work since training data must be generated, reading algorithms. data, train the network itself and test its operation experimentally in our laboratory.

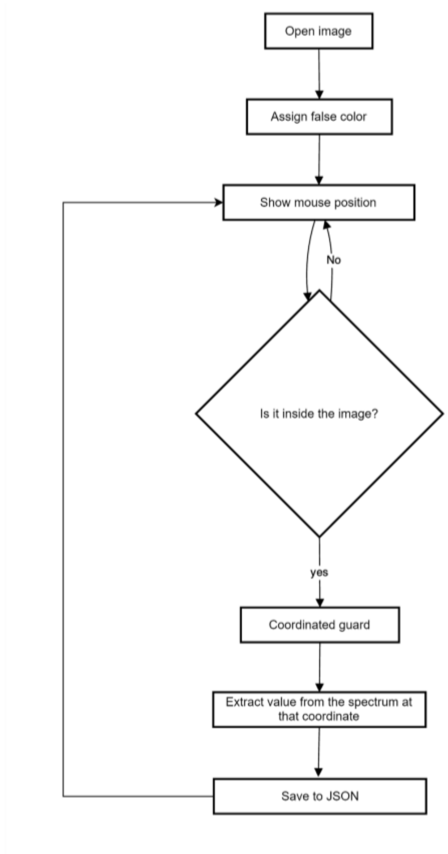
2.3.2.1 Data acquisition

One of the most important parts is the preparation of the training datasheet to use for network training. This must be carefully chosen otherwise the results may be wrong. To do this, from a hyperspectral image with ranges between 2500 and 5500 nm, valuees will be manually extracted values in random regions within each plastic. This will be saved in a JSON to facilitate the handling of this data. The CSV format was evaluated; however, JSON is easier to handle. So an algorithm had to be implemented that would open the hyperspectral image, represent it in false color so that it could be represented and observed with the human eye. After this, through the python libraries that image must be represented in false color and extract the spectra of the selected pixel with the cursor by using the mouse

Finally, this spectrum must be tagged and saved in a JSON within a training data folder

This acquisition process was repeated for all the plastics available in this first sample, i.e. ABS PS and PE, in addition a fourth element was obtained that would discern between the background and the samples.

For storage, values were saved in a JSON with the following structure:




```
{
"Type": "ABS",
"Additive": "ABS",
"Bands": 154,
"Spectre": []
}
```

Figure 34 Flowchart made for the manual taking of training values of the spectra in the hyperimage provided by SPECIM

As it is a classification problem, the algorithm needs to learn the types of plastics available to associate that spectrum with that plastic, however, mathematical algorithms only understand numbers so these are ABS=0, PS=1, PE =2 and background =3.

In this way, the training method consists of introducing a spectrum at the input and at the output giving it a value that represents the type, in this way internally the program is adjusted, minimizing the error between what it obtains and what it should obtain.

Figure 35 Diagram of how plastic would be processed

2.3.2.2 Architecture

A neural network with a "Sequential" type capase arrangement is used, to stacks one layer after the other, this arrangement being one of the simplest that exist. In addition, the type of layer used was "Dense" type layers whose input size was reduced. For the activation function a "ReLu" function was selected except for the last layer that was decided to use a "SoftMax" since a classification problem is approached, and this type of activation function is the optimal for this type of work.

A summary of the architecture for the processing of the spectra and the classification of plastics, it would be as follows:

Table 1 Network architecture used

N	Kind	Input size	Activation function
1	Dense	154	ReLu
2	Dense	64	ReLu
3	Dense	64	ReLu
4	Dense	32	ReLu
5	Dense	1	Softmax

For the optimization of the model, the optimizer "Adam" was used and for the loss function "sparse_categorical_crossentropy", a Learn Rate of 0.01, a Batch Size of 80 and 500 epochs, were used.

If the values of Learn Rate are modified or in the times seeking to minimize the error as much as possible phenomenon of "overleafing" occurs when the error during training is so small that the algorithm only knows how to classify the data with which it has been trained since a slight deviation of the input data causes the network not to recognize the input data. Therefore, during training precision of 100% is not possible since the phenomenon of overleafting would occur.

The architecture, epochs, activation functions, type of layers, etc. have been chosen through trial and error with the objective of minimizing the error that occurred during network testing.

2.3.2.3 Processing algorithm

After having trained and generated the weights of the neural network, it will interpret it as a black box in which an array of values are entered that represent a spectrum and output is the type. A way to apply this algorithm to a complete image is the next step.

To do this, a python library that enable a watchdog that monitors the status of a folder in search of new events is planned to create a script to constantly monitor the status of that folder following the following workflow:

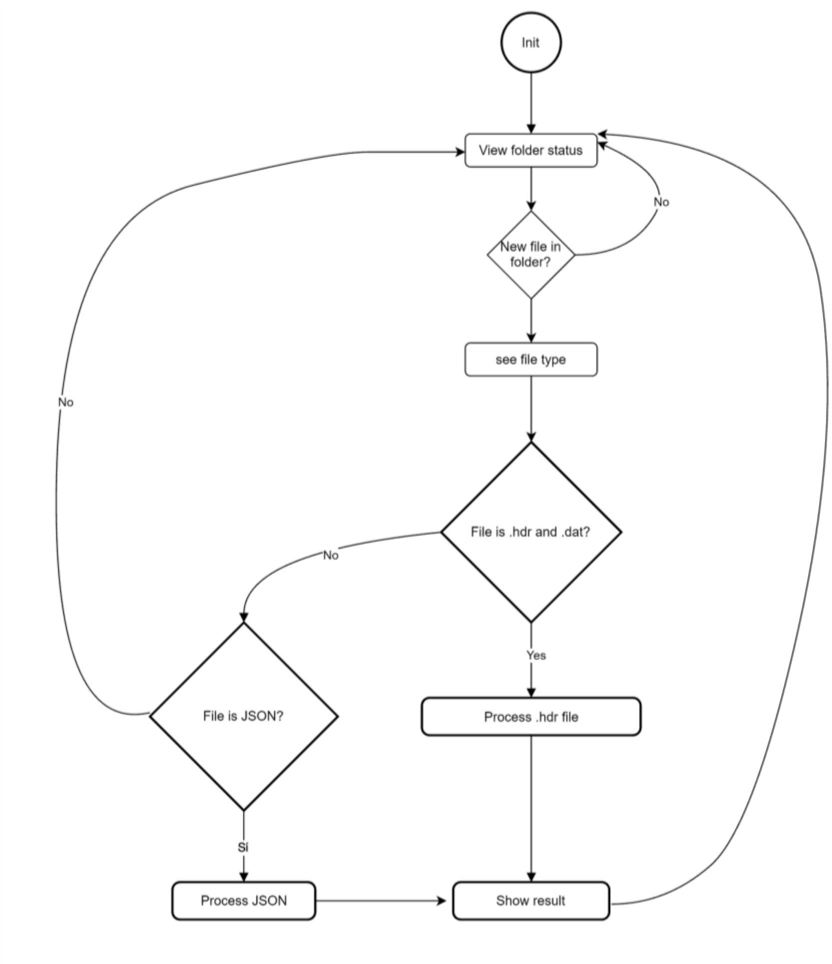


Figure 36 Flowchart to create the script that allows data to be processed independently of the hardware used

To prepare the data for training JSON format was used, to test the precision of the algorithm, initially the processing algorithm only supported JSON, after having verified that the precision was acceptable, to modify the processing code so that it distinguished one type of data or another and maintain the initial structure of the algorithm with python watchdog but processing more complex data such as complete hyperspectral images. The only difference is the "Process .hdr file" function which opens the hyperspectral image and goes through pixel by pixel reading the spectrum, introducing it into the network and generating at its output one type of plastic or another depending on the spectrum read in each pixel, generating at the output a matrix of the same size as the layers of the input image but with a single dimension in which instead of having the values of the spectra per pixel to have the type of plastic.

The "Process JSON" function simply reads a JSON file, extracts the "Spectrum" field, passes it to a numpy array and enters it into the network, resulting in the type of plastic that the network detects based on a spectrum.

This way of processing the information has been sought for algorithm independent of the hardware, that is, all the cameras export the data in .dat and .hdr formats, however the way in which they are operated is not, so an algorithm that manages the camera which is particular to each manufacturer and another processing algorithm running in a separate thread listening in a specific folder are needed to separate the processing algorithm from the algorithm in charge of managing the hardware.

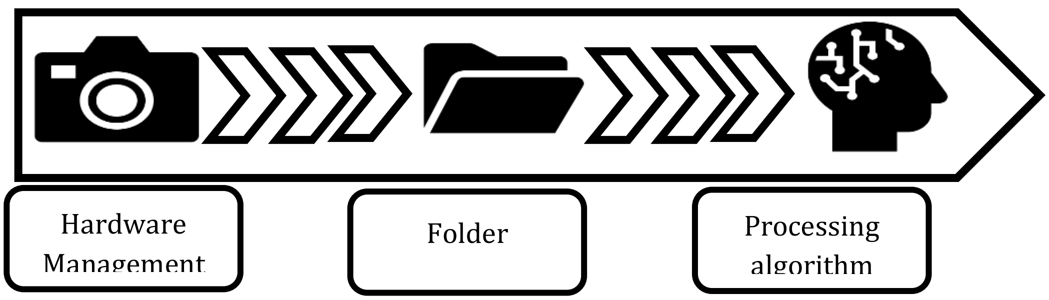


Figure 37 Data flow between the camera and the neural network

2.6.2.4 Results

Putting the algorithm to work, first processing a single spectrum in the form of JSON, extracted manually and after processing an entire image, obtaining good results in terms of precision in about 98% of the images, 98 correct out of 100.

It is noteworthy that plastics, despite being black, are spectrally very different, so it is not difficult for the neural network to differentiate one type from another. Furthermore, since it is a fixed sample, that is, the conditions of angle, light and position of the plastics are constant, in addition to the fact that photos of large pieces were taken and in a static manner, conditions that can improve the results considerably and maybe this accuracy may be lower in real processing conditions. The algorithm is still slow, as it takes 700 ms to process a spectrum and becomes unfeasible to process as many times as there are pixels in the image.

$$\text{Number of pixel per image} = 980.000 \text{ px}$$

$$\text{Processing time per pixel} = 700 \text{ ms}$$

$$\text{Processing time per image} = 980.000\text{px} * 0{,}7\text{s/px} * 1\text{h}/3600\text{s} \approx \mathbf{19h}$$

These results make us reconsider the way in which information is processed, in search of reducing processing time so that the recycling machine is not the bottleneck of the production process.

2.3.3 Algorithm 2

After having evaluated the time it takes to process the image, the algorithm was modified to process the complete image, maintaining the algorithm that monitors the folder and maintaining the neural network.

Not all the pixels were processed but only those that were necessary. For example, it does not make sense to process the background pixels, so they are pixels that the network should not process, so the algorithm would considerably reduce the processing time. At the same time, we do not believe it is necessary to process the entire body of the plastic object, so only a couple of points that describe the type of plastic that is being classified would be processed. The first thing to do is to extract the background from the image.

2.3.3.1 Extract background

Working with images that represent colors outside the visible range, cannot represent the virgin image, this causes the RGB colors to be assigned to certain bands of the spectrum, for example to read the 2556nm band a scale change between 0 and 255 is needed and this represents the color red, and the process is repaeated with green and blue. By applying this to all the pixels of the hyperimage an image in RGB is composed.

Now it's time to go to grayscale since it is mandatory to be able to do morphological operations on the image, necessary to be able to extract the background and isolate interesting regions within the image.

Having passed the hyperimage composed of 154 n X m matrices, we have obtained an n X m X 1 image, facilitating processing.

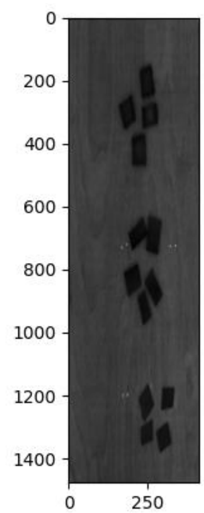


Figure 38 Image of plastics in false color

When the hyperimage is represented in gray scale, the algorithm must differentiate the background and the object . The background represents the greatest number of pixels, that is, if the object and background pixels are counted, the number of pixels that the background represents is much greater.

If we make the histogram of this image it will result in the following graph

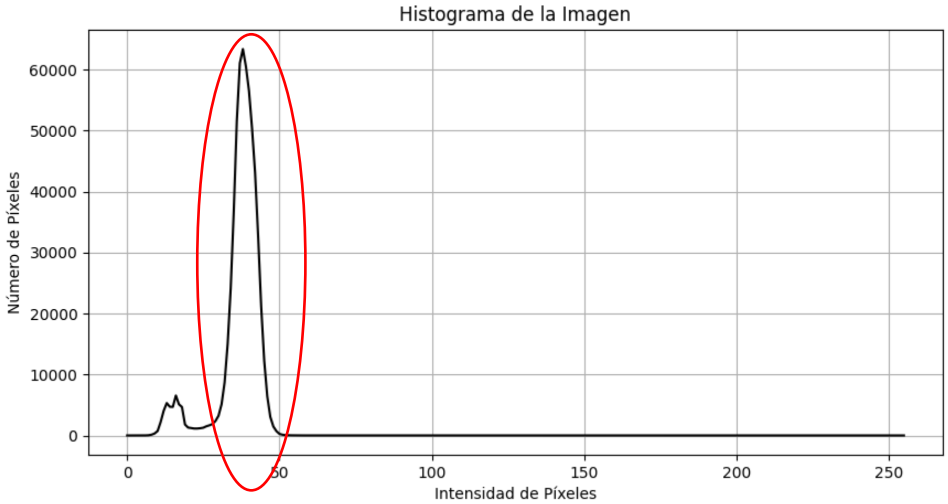


Figure 39: Identificaiton of background

The gray scale near the value 45 is the one with the most pixels, so the background is represented by gray values around that peak, so the image values near that peak +- threshold are 0 and the rest 1, obtaining a result of an image with 1 in the plastic object and 0 in the background.

To obtain better results when classifying, the image is processed to eliminate noise and certain areas such as objects, being background. This is done by applying a morphological operation called opening. This is a mathematical operation applied to the image that improves the result of the binarization.

After this, the different areas of the image which are not the background need to be identfied. For this, the OpenCV library has functions which label and generate an automatic segmentation of the image, for using the function cv2.connectedComponentsWithStats(imagen.astype(np.uint8)) which gives an array of tuples at the output with the number of regions, the regions, the boundig box and the centroids of these regions.

With this information extract random points are extracted within these regions to eliminate unnecessary pixels to reduce image processing time.

This is achieved by the algorithm shown in Fig.40.

2.3.3.2 Results

This algorithm is currently under evaluation. Reducing the number of points proved to improve processing time by reducing the size of data to process. However, we need to continue testing this algorithm.

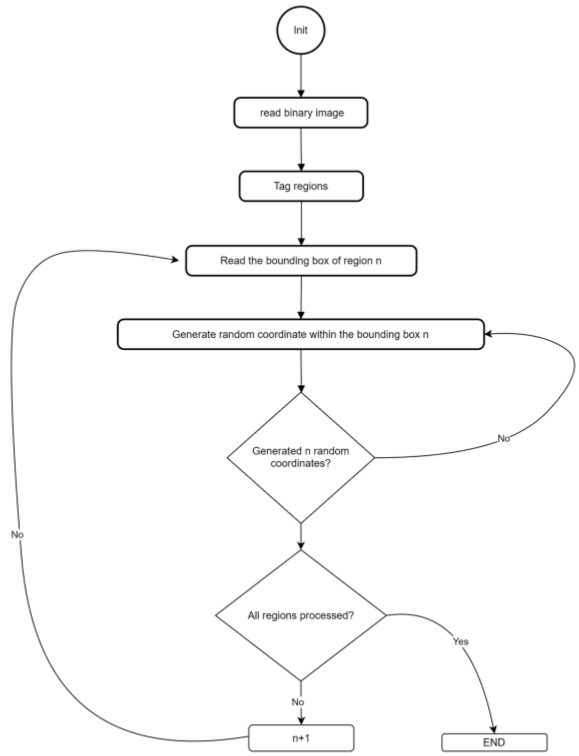


Figure 40: Algorithm for

3 Conclusion

This document aims to provide an overview of the tool that Canonical Robots is designing. It is a complex task that involves a lot of research and hardware, leaving the software in the background.

The the steps followed to date, and the conclusions obtained, tests carried out, meetings held with experts and the results obtained are recorded.

4. annexes

Company	SPECIM	BLACKINDUSTRY	EVK	PHOTONIC SCIENCE	XENICS
Type	Lineal	Lineal	Lineal	No Lineal	Lineal
Model	FX17	SWIR 1.7 MAX	HELIOS EC32	Cooled VGA SWIR InGaAs Camera	Lynx R Series
Apperance					
wavelenght	900-1700 nm	900-1730 nm	929-1700 nm	900 - 1700 nm	900 - 1700 nm
Frame Rate (FPS)	670	450	446	7200	40000
Vertical Resolution (Pixel)	X	x	x	512	x
Horizontal Resolution(Pixel)	640	1280	320	640	1024
FOV(º)	38	38	38	38	38
HEIGHT (H)(mm)	3298	3298	3298	3298	3298
Size object (R) (mm)	6	3	13	6	4
MAX Conveyor Speed(cm/s)	419	141	558	4500	15625
Cost (euros)	40000	30000	29.660	No response	No response

Width conveyor belt (mm)	1000
Security constant	4

This project has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No 101092295. The herewith information reflects only the author's view. The European Commission is not responsible for any use that may be made of the information herewith included.