Development of a Low-Cost Optical System for Monitoring Plastics in Irrigation System Grids

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***Abstract*— The plastics incorporated into the irrigation channel of agricultural plots is a major problem due to the outline produced by these in the gratings present in these systems. In this article, we present a low-cost system based on artificial intelligence to monitor the presence of plastics in the gratings of agricultural irrigation channels. For this purpose, an experiment has been carried out using a fish tank, where a grid with bag sections has been placed. Different photographs were taken at 10 cm from the camera, with 0 g, 5 g and 10 g of soil added. Once the images were obtained, the Matlab programme was used to process them and obtain histograms of the red, green, and blue bands. The best results are shown in the image with 0 g of soil and 5 g of soil. The verification carried out with 0 g of turbidity shows that the % of pixel number of the grids are above the limit of 5%, the maximum value for the grids is 84.08%, being the percentage of pixel number of the bags below this limit with a maximum value of 0.09%.**

Keywords—Optical system; plastic monitoring; irrigation system; image processing, RGB.

I. INTRODUCTION

Plastics are synthetic materials produced by synthetic or semi-synthetic organic polymers [1]. More than 8.3 billion metric tons of plastics have been produced since the 1950s and the proliferation in their use has been exponential [2]. Plastics are inexpensive, versatile, lightweight, and durable. This fact makes plastic containers used to store a multitude of different materials, from objects to food, because they act as a barrier preventing contamination. Besides, they support the family economy and food security by minimizing post-harvest losses, increasing shelf life and storage capacity [3].

The great versatility of these makes their production increase every day, making them one of the most important pollutants at the marine and terrestrial level due to their difficult degradation. The fact of its prevalence in these environments makes it become a worldwide problem. One of the main problems is that it prevents the proper growth of plants, as well as that of crops, generating agricultural pollution [4].

Plastics can also be a major problem for the irrigation system because the accumulation of plastics in the gratings of agricultural irrigation canals causes runoff, reducing the irrigation flow. In addition to a reduction in water flow, the accumulation of these plastics indirectly also causes other materials, such as leaf debris or branches to accumulate on these gratings, allowing the flow to increase in one part of the grating, causing overflow and loss of water. This loss of water may be relevant, since Agriculture accounts for about 33% of total water use in Europe, and water use is most intensive in southern parts of Europe, where 80% of total water consumption goes to crop irrigation [5].

The most commonly used method for the detection of plastics is the satellite method. This system is especially suitable for open surfaces with a large surface area. In this case, satellite images are not suitable because the irrigation channel of agricultural plots is a small system, which results in the inefficiency of this type of method. In addition, satellite imagery is often very expensive and not affordable for farmers [6]. In this paper, we propose a sensor for detecting the presence of plastics in the irrigation grids to control, detect, eliminate and prevent plastic bags, bottles, or other plastic waste, dumped by humans, from damaging not only the crops, if not our own body. The proposed system will be of great use to farmers, as it will provide a plastic detection tool to prevent outbreaks in irrigation canals. It will be useful to ensure optimal water flow within the system. To do this, a camera will be installed in the irrigation grid, which will be able to detect the presence of plastics and differentiate it from other materials. Artificial intelligence will be used for this, through image processing. In this way, this sensor will send an alert to the user of the said grid of the presence of plastics, so that the user can remove them, avoiding not only the contamination of their growing area but also the subsequent dumping of said plastics in more advanced areas of a said chain like the seas, oceans, or our bodies.

The rest of the paper is structured as follows. In Section II, we explain the related work. The test bench is presented in Section III. Section IV shows the system proposal for our prototype. The results are described in Section V. Then, Section VI displays the verification of the experiment. Finally, in Section VII, we expose the main conclusion and future work.

II. RELATED WORK

In this section, we analyze the different methods used to detect the presence of plastics in aquatic environments, although it should be noted that so far, no detection system has been found in irrigation grids for agriculture.

In 2018 Karaba et al. [7], using equipment mounted on a C-130 aircraft, which captured SWIR Red, Green, and Blue (RGB) and hyperspectral images, detect plastics in the ocean. However, this technique requires a large infrastructure, as well as being very expensive. They established that the absorption of ∼1215 and ∼1732 nm can be used for applications in the detection of ocean plastics from spectral information. Secondly, Biermann et al. in 2020 [8] demonstrated that floating macroplastics are detectable in optical data acquired by the sentinel-2 satellites of the European Space Agency (ESA). In addition, these could be distinguished from natural materials like algae. On the other hand, they detected patches of materials on oceanic surfaces, which employing the Floating Debris Index (FDI). Taking advantage of this way, the spectral information to differentiate the macroplastics. The classification was carried out with 86% precision. Recently, Iri et al. [9] in 2021, have developed an optical system capable of detecting microplastics in water. The developed sensor is based on a low-cost system based on a spectrophotometer. The system they use is capable of detecting microplastics below 0.015 p / v.

In 2020, a methodology was carried out to provide a rapid and cost-effective characterization and quantification of the transport of floating macroplastics in the Rhine river by Vriend [10]. This study is based on visual observation, combined with passive sampling to arrive at an estimate of the transport of macroplastics as well as the most abundant types of plastics in this river. In this way, they studied the advantages and disadvantages of current sampling systems and established a new perspective for new monitoring systems. In the same year, Van Lieshout et al. [11], presented a method for the detection of plastics. This system is based on an automated system monitoring that detects said contamination. They installed cameras on bridges along the river, and from the images taken and through deep learning; they were able to estimate the plastic density. Its system is capable of distinguishing plastics from environmental elements.

Studies on the hyperspectral reflectance of virgin plastics degraded by nature and submerged in water at different concentrations and depths of suspended sediments have been carried out by Moshtaghi et al. in 2021 [12]. Besides, more analysis has been carried out on the different types of existing polymers to had better understand the effect of water absorption. The results show the importance of using spectral wavebands in both the visible and Short-Wave Infrared (SWIR) spectra for debris detection, especially when plastics are damp or slightly submerged, which is often the case in environments natural aquatic.

Although some of these systems are based on optical systems, at the moment no system has been found that is established in a fixed point, and that sends alarms simply and easily to the farmer himself. In addition, the systems found are often expensive systems that require sophisticated devices such as airplanes, satellites, among others. It is for this reason that the sensor that we have developed, in addition to being cheap, easy to use, and allows monitoring in real-time what is happening at a specific point.

III. PROPOSAL

Because the presence of plastics or objects in the irrigation channels of pipes can cause important problems and damages in systems, it is important to determine if some element is hindering the normal flow of water. To do that, we propose the use of a camera and an intelligent algorithm to periodically analyse the status of the grid. This section describes the decision algorithm used to detect if plastic is present in our grid.

A. System description.

In order to detect if plastic or object is blocking or hindering the flow of water through a grid, we propose the use of a camera to take pictures of this grid when water is being used. As Figure 1 shows, the camera is inside the water channel. The system also includes a turbidity sensor [13]. After taking a picture, the image is wirelessly transmitted to a node that will be in charge of processing the received image. Although there are several techniques for data computing, our system performs a local computation (edge computing). In this sense, the replies required to solve the problem of plastic presence in the grid are faster than techniques such as fog computing or cloud computing.

When plastic is detected, the node creates an alarm and sends it to the server application. The server is in charge of warning the users or farmers through a Graphic User Interface (GUI) previously installed in the farmer's Smartphone. The farmer can stop the irrigation process and remove the plastic from the grid.

On the other hand, the whole process is stored in a database join with other possible parameters monitored in the crop. The images are also stored in the database with the results of processing them. With that, we are creating a database to permit the system to learn from previous experiences for generating more accurate decisions in further situations.

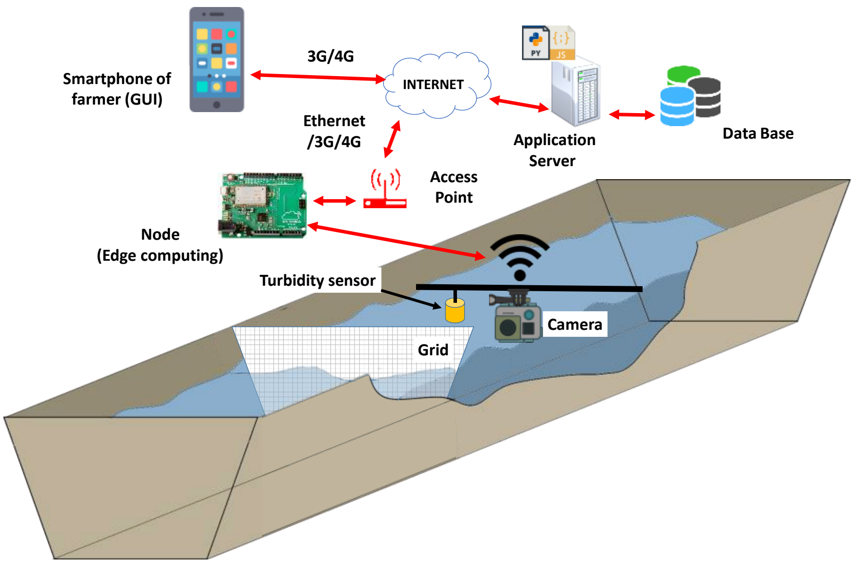

Figure 1. Proposed system.

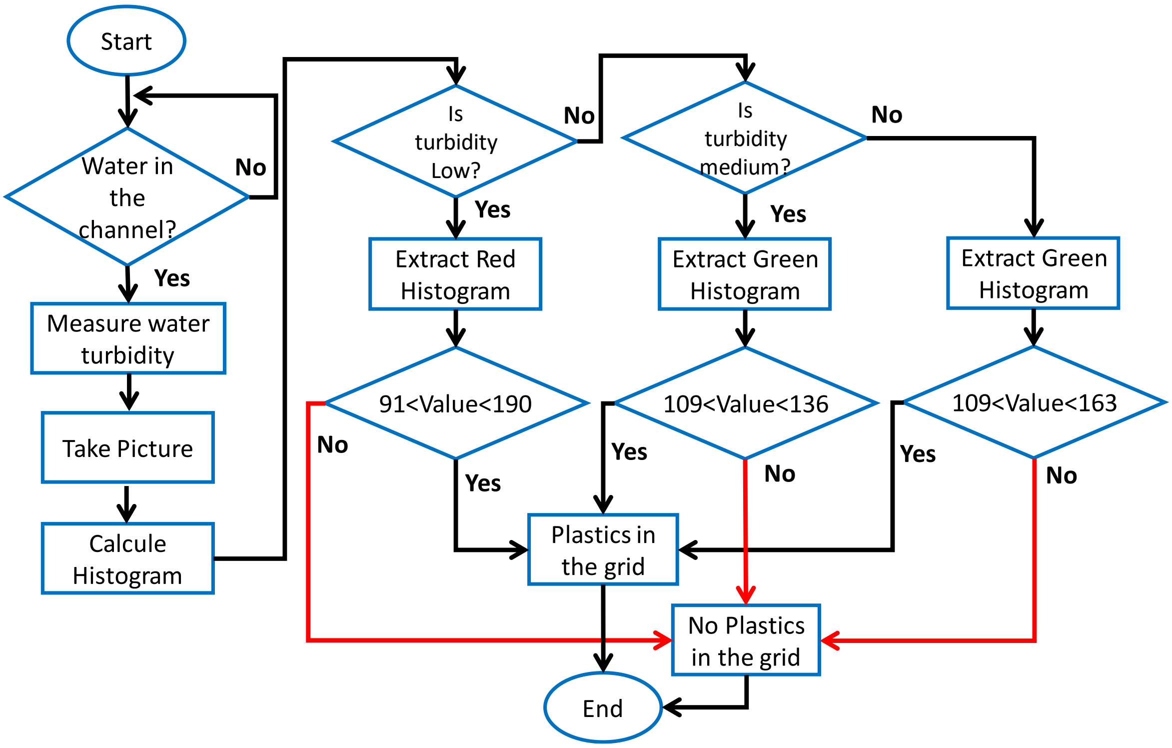

Figure 2. Decision Algorithm

B. *Decision algorithm.*

In order to be able to detect the presence of plastics in the grid, it is important to recognize the grid shape from the plastics that do not usually present the same shape. It is possible to apply complex AI-based algorithms to firstly detect the shape of the grid and subtracts it from the obtained image. In our case, we will distinguish the grid by analyzing its RGB components from the RGB components of plastics. Figure 2 displays the decision algorithm that we propose.

When the irrigation process is started, the system checks if there is water in the channel. After that, the level of turbidity is measured. According to the turbidity level, the thresholds for detecting plastics on grids will change. The next step is to take the picture and calculate its RGB histogram. When low turbidity is detected, the red histogram is considered. In this case, the biggest contributions in pixels should be concentrated between 91 and 190. When a medium turbidity level is detected, the green histogram is analysed. In this case, the biggest contributions in pixels should be concentrated between 109 and 136. Finally, if high turbidity is detected, we have also considered the green turbidity. In this case, the biggest contributions in pixels should be concentrated between 109 and 163. Inside these ranges, the system will inform on the presence of plastics. In any other case, the system will tag the measures as non-plastic in the grid.

IV. TEST BENCH

In this section, we present the materials used for the experiment. Besides, the methodology used for data collection is described.

A. *Materials*

For the experiment, a rectangular glass fish tank with dimensions of 24.5 cm high, 26 cm wide, and 50 cm long were used. A white plastic grid 23 cm high and 25 cm wide was used to simulate the presence of a grid. Two pieces of plastic supermarket bags were placed on the grid to represent the plastic waste that humans throw into the environment. Soil with a composition of 4.3 % sand, 67.3% silt, and 28.4 % clay was used as a turbidity-enhancing compound. In order to stabilize the light input in the tank and to obtain a homogeneous light distribution, a tank light was used. In addition, a Xiaomi Red Mi Note 6 Pro mobile phone with a 20-megapixel sensor camera was used to capture the images required for the subsequent study.

Finally, a black blanket was placed on top of the tank to limit the entry of external light and thus reduce interference to a minimum. Figure 3 displays the experimental setup. The grid used and the arrangement of the two pieces of plastic used can be seen. The grid is located at 10 cm distances from the fish tank glass on the horizontal axis. Besides, the homogeneity of the light distribution can be observed by placing a fish tank lamp on top of the tank.

Figure 3. Experimental tank.

B. *Methodology*

The implementation of the experiment has two phases. The first is based on the experiment itself, where the necessary images are taken. The second is the processing and analysis of these images in order to obtain the different histograms of these images and to be able to differentiate between the grid and the plastic bag in different conditions.

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For the first phase of the experiment, images are taken of a grid with two pieces of a plastic bag at different distances and with different turbidity. To do this, we start by filling the tank with 37 L of tap water at a height of 18.5 cm to 6 cm from the top edge of the tank. Then we introduce the grid with the plastic bags. The images are always taken from a fixed point, from the side of the tank. In addition, each round of images is captured while a black blanket to block outside light permanently covers the tank. Photographs are taken by placing the grid at 10cm from the camera. This is repeated in triplicate, with 0 g of soil, 5 g of soil and 10 g of soil to increase turbidity.

Once the images have been obtained, we start with the second phase. In this part, the images obtained are processed and analysed. For this, we use the Matlab software [14] with which we can acquire different histograms in red, green, and blue. Figure 4 presents pseudocode used in the programming process of the images, obtaining the histograms of different colours, as well as the tables with their respective data.

To obtain the necessary information, we choose 3 bag sections and another 3 pieces of the grid from each image and we introduce them into the software. Matlab generates three histograms in red, green, and blue for each section of the image entered, with their respective data. Once these histograms are obtained, we put them together to obtain the different ranges of pixel values for bag and grid, in order to differentiate between them. Figure 5 presents the image where the grid is 20 cm from the camera. Image a) displayed picture without soil and b) image represents water with 10 g of soil to increase the turbidity. It can be seen how the pockets begin to diffuse and start to look like part of the grid.

V. RESULTS

In this section, the results obtained after treating the images with the Matlab software are presented. The different histograms for each image are evaluated to verify the ranges of pixel values for the bag or grid.

A. *The image at 10 cm from the camera*

Figure 6 displays the histograms obtained from the image captured at 10 cm from the camera, without turbidity. Section a) represents the blue histogram, b) the green histogram and c) the red histogram. Besides, each of them shows the graphical representation of three pieces of the bag (in reddish colours) and three pieces of grids (in bluish colours). It can be seen that in the three histograms, it is easy to differentiate in which pixels and values the grid or bag is located. The most representative graph is c) where we can find the presence of grid between pixel values from 1 to 90 and from 91 to 190 for the presence of pockets. The maximum pixel percentage for grids is 4 % and 5.3 % for the bag. The results show a noticeable difference between the grid and the plastic bags, as the pixel values are different in the different pixel ranges. These results show that in non-turbidity conditions, the system is able to differentiate between the two objects.

```
Function [Hist_RED, Hist_GREEN, Hist_BLUE,] = Read_Comp_Image
(Comp_RE, Comp_GR, Comp_BL, Col, Row]
//Calcule Histogram Red
Repeat
        vector_RE [i]=0    // Create_vector_RED
Up to (i=256)
Repeat
        Repeat
                Read Value= Comp_RE
                vector_RE [i]= Value
                Comp_RE++
        Up to (Column == end)
Up to (Row == end)

//Calcule Histogram Green
Repeat
        vector_GR [i]=0    // Create_vector_GREEN
Up to (i=256)
Repeat
        Repeat
                Read Value= Comp_GR
                vector_GR [i]= Value
                Comp_GR++
        Up to (Column == end)
Up to (Row == end)
```

Figure 4. Pseudocode used to get RGB histograms.

B. *Imagen at 10 cm from the camera with 5 g of soil.*

In the case of Figure 7, it represents the values obtained for the blue, green, and red band of the image at 10 cm from the camera with 5 g of soil added to the water. Section a) represents the blue histogram, b) the green histogram and c) the red histogram. In addition, each of them shows the graphical representation of three pieces of the bag (in red colours) and three pieces of grids (in blue colours). It can be seen that in the three histograms, it is hard to differentiate in which pixels and values the grid or bag is located. In this, case the best section is the b) with the green band. We can observe that parts of grids 2 and 3 can be distinguished from the presence of bags. The presence of the grid is located between the values 55 to 105, with a maximum pixel percentage of 3%. The results show that the system is able to differentiate some pieces of bag. This is because the turbidity, together with the dark edges of the tank, could have caused interference in differentiating between the objects.

C. *Imagen at 10 cm from the camera with 10 g of soil.*

Figure 8 represents the values obtained for the blue, green, and red band of the image at 10 cm from the camera with 10 g of soil added to the water. Section a) represents the blue histogram, b) the green histogram and c) the red histogram. In addition, each of them shows the graphical representation of three pieces of the bag (in red colours) and three pieces of grids (in blue colours). It can be seen that in the three histograms, it is hard to differentiate in which pixels and values the grid or bag is located. In this, case the best section is the b) with the green band. We can observe that parts of grids 2 and 3 can be distinguished from the presence of bags. The presence of the grid is located between the values 109 to 163, with a maximum pixel percentage of 12.5%.The results show that at higher turbidity the system starts to have difficulties in differentiating between different objects. In addition, the reflections produced by the tank used produce more interference.

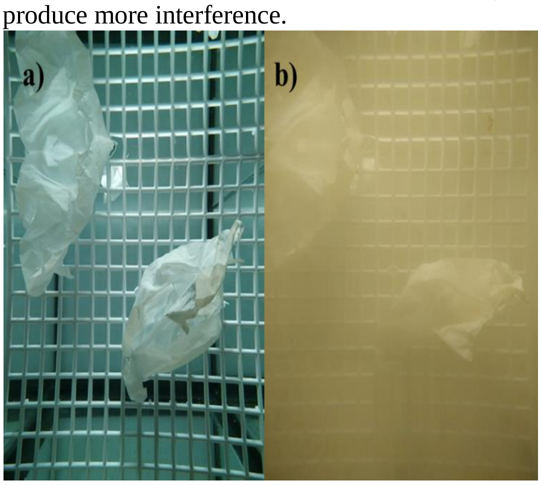

Figure 5. a) Grid 20 cm from the camera; b) Grid 20 cm from the camera

with 10 g of soil added to the water;

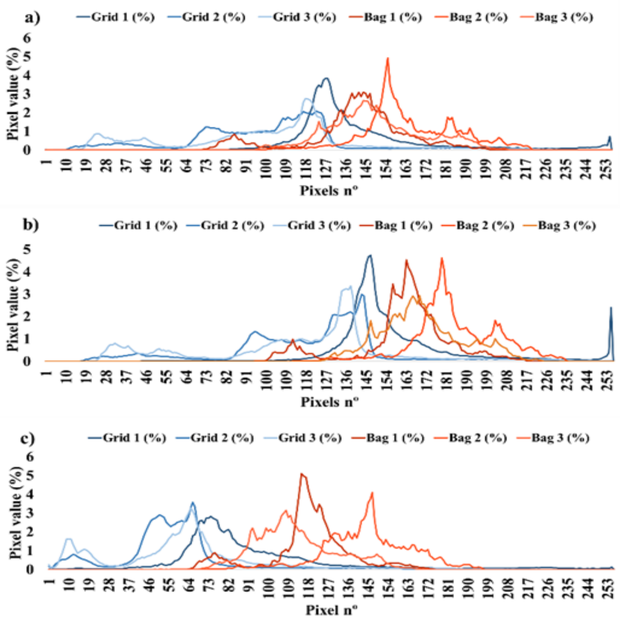

Figure 6. a) Histogram of the blue band at 10 cm; b) Histogram of the green band at 10cm; c) Histogram of the red band at 10cm.

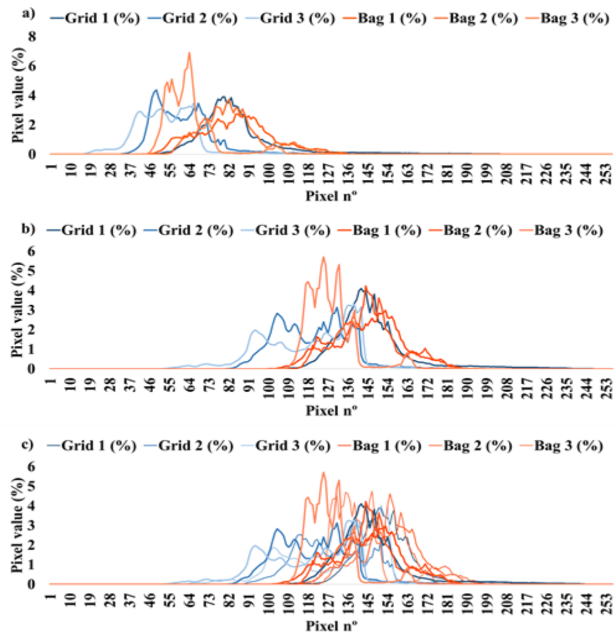

Figure 7. a) Histogram of the blue band at 10 cm with 5 g of soil; b) Histogram of the green band at 10cm with 5 g of soil; c) Histogram of the red band at 10cm with 5 g of soil.

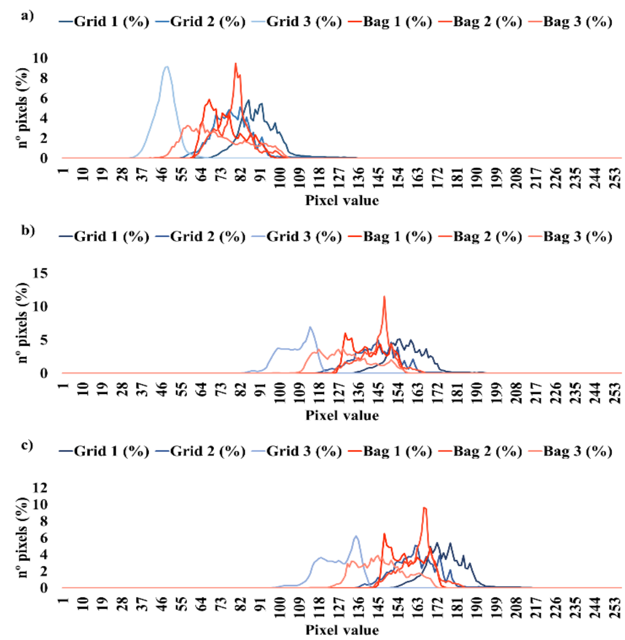

Figure 8. a) Histogram of the blue band at 10 cm with 10 g of soil; b) Histogram of the green band at 10cm with 10 g of soil; c) Histogram of the red band at 10cm with 10 g of soil.

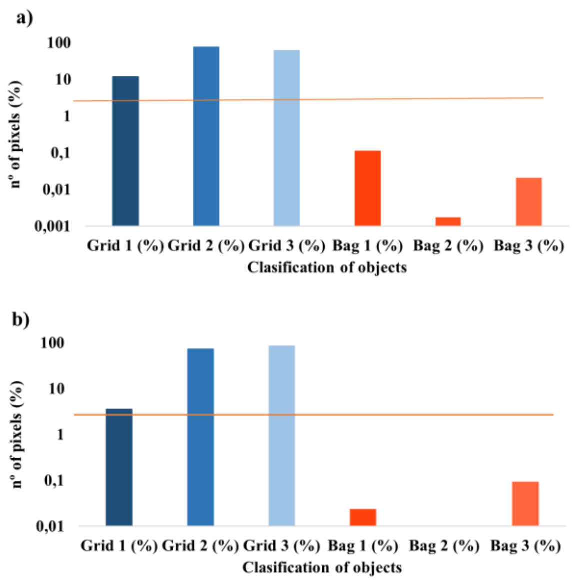

Figure 9. a) Analysis of image at 10cm with 0g of soil; b) Verification Analysis of image at 10cm with 0g of soil.

VI. VERIFICATION

To determine the effectiveness of the developed system, we conducted a verification. For this purpose, the image at a distance of 10 cm without added soil is used. New sections of the image are taken and their values are obtained. Figure 9 shows the differences between the grid and the bag. Section a) represents the values taken in the experiment, where it can be seen that the percentage of pixels above the 5% limit are considered part of the grid and below the bag. Graph a) displays that the grids show a maximum pixel % of 74.8% in grid 2, and a maximum pixel % of bags of 0.02%. In addition, section b) represents the verification performed, taking other different pieces of grid and bag. This graph shows a maximum pixel % of 84.08% in grid 2 and a maximum pixel % of bags of 0.09%.

The results demonstrate the similarity of the data, showing the presence of grating above 5 % of the number of pixels.

VII. CONCLUSION AND FUTURE WORK

The presence of plastics in the agricultural irrigation system represents a major problem due to the possible outlines produced in the grids of the same, producing a decrease in the irrigation flow, as well as the need for control in situ for its solution.

In this paper, we propose a system to monitor the presence of plastics in the gratings used in irrigation channels for agriculture. We have determined that it is possible to differentiate between bags and the grid up to 5g of added soil. It has additionally been found that at higher turbidity the results are not optimal due to the dark edges and reflections possibly produced by the fish tank. The proposed system is based on the application of artificial intelligence, being of great help, in this case, to be able to differentiate and learn about the presence or absence of plastics in the grid.

In future work, we want to test at different distances. We will extend the number of objects to be detected. In addition, we will use leaves and other types of waste to perform the experiment, to provide to our system more information about the different objects that could be presents in irrigation channel grids.

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