Comparison of Single Image Processing Techniques and Their Combination for Detection of Weed in Lawns

Lorena Parra [(1), (2)], Mar Parra [(1)], Virginia Torices [(3)], José Marín [(3)], Pedro V. Mauri [(1)], Jaime Lloret [(2)]

[(1)] Instituto de Inv. para la Gestión Integrada de Zonas Costeras (IGIC), Universitat Politècnica de València (UPV). C/ Paranimf, 1, 46730 Grau de Gandia, Gandia

[(2)] Instituto Madrileño de Investigación y Desarrollo Rural, Agrario y Alimentario (IMIDRA), Finca El Encin, Autovía del Noreste A-2, Km. 38.200, 28805 Alcalá de Henares, Madrid

[(3)] Universidad Politécnica de Madrid. Escuela Técnica Superior de Ingeniería Agronómica, Alimentaria y de Biosistemas. Av. Puerta de Hierro, 2, 28040 Madrid

Email: loparbo@doctor.upv.es, maparbo@epsg.upv.es, virtorices@gmail.com, jmarin@areaverde.es, pedro.mauri@madrid.org, jlloret@dcom.upv.es

***Abstract*— The detection of weeds in lawns is important due to the different negative effects of its presence. Those effects include a lack of uniformity and competition for the resources. If the weeds are detected early the phytosanitary treatment, which includes the use of toxic substances, will be more effective and will be applied to a smaller surface. In this paper, we propose the use of image processing techniques for weed detection in urban lawns. The proposed methodology is based on simple techniques in order to ensure that they can be applied in-situ. We propose two techniques, one of them is based on the mathematical combination of the red, green and blue bands of an image. In this case, two mathematical operations are proposed to detect the presence of weeds, according to the different colorations of plants. On the other hand, we proposed the use of edge detection techniques to differentiate the surface covered by grass from the surface covered by weeds. In this case, we compared 12 different filters and their combinations. The best results were obtained with the Laplacian filter. Moreover, we proposed to use pre-processing and post-processing operations to remove the soil and to aggregate the data with the aim of reducing the number of false positives. Finally, we compared both methods and their combination. Our results show that both methods are promising, and its combination reduces the number of false positives (0 false positives in the 4 evaluated images) ensuring the detection of all weeds.**

Keywords- Grass lawns; weeds; image processing; RGB bands; edge detection; drone.

I. INTRODUCTION

In order to maintain a great appearance in grass surfaces, certain requirements need to be addressed. The use of technology can help in its monitoring [1]. Due to the activities that are carried out on the grass or around it, the grass suffers from compaction and the leaves are broken. Some of the activities performed on the lawns in residential areas or in public gardens are certain sports, entertainment, and enjoyment. The users of the lawns demand a series of requisites, being the most important one the visual aspect of the lawns. The visual aspect can be expressed as the uniformity of the lawn, the greenness of the grass and the absence of grass patches. Moreover, the lawns should be maintained with a low level of inputs [2].

The existence of weeds in the lawn is a problem. On the one hand, the weed presence implies a lack of uniformity on the surface. This lack of uniformity is the first cause of disappointment for users. On the other hand, the weeds will generate competition between them and the grass species. For this reason, it is necessary to carry out specific actions to solve the weed problem as soon as possible. Despite the fact many studies showed the benefits of spontaneous plants in the urban lawns, users still prefer the uniformity of the grass [3-5].

It is crucial to detect the appearance of weed during the first days. Otherwise, the weed can infest huge areas of the lawn, and it will be difficult to eradicate them. Nowadays, the best available techniques to detect weeds are aerial images or the visual inspection of the lawns. The first option, the use of satellite images, offers multispectral images. Nonetheless, they have small spatial resolution and small temporal resolution. Thus, when we detect the weeds with the satellite image it may be too late and it would be necessary to apply the phytosanitary treatment to a large area. The second option, the visual inspection, is useful for small areas like a private garden. Nevertheless, for big areas like golf courses or big public gardens, this solution is not applicable. Therefore, the use of images obtained with drones and their analysis can be a solution for large surfaces [1]. The use of image processing is widely used in many different areas and for countless purposes. In agriculture, it has been used for illness detection [6] and for fruit maturity evaluation [7]. In aquaculture, it has been used for feed falling detection [8]. Moreover, it is used for face detection [9] and car license plate identification [10].

The aim of this paper is to present the use of image processing techniques for detecting the presence of weeds in lawns, which will be part of a system for garden monitoring described previously in [11]. Thus, a series of images were obtained from different lawns with the presence and absence of weed. The images were taken under different solar conditions. Different grass species and different weed species appear in the images. Part of the images will be used to evaluate the different techniques and methods included in our system and the rest of them to verify our findings. Two methodologies are tested, the Red-Green-Blue (RGB) band combination (or RGB methodology) and the edge detection filters. The goal is to use this methodology to automatize the monitoring of lawns in terms of weed detection. Therefore, it will be possible to detect the weed and apply the phytosanitary products only in the affected area. The operation of applying the phytosanitary product is not the focus of this paper. First, we test each methodology, including pre-processing to remove the soil from the analysis and post-processing to minimize the number of False Positives (FP). Then, we compare the results of both techniques and their combination.

The rest of this paper is organized as follows. Section II presents the related work. Section III describes the proposal. The methods, band combination and edge detection are described in Section IV. Section V addresses the obtained results of each separated methodology and its combination. Section VI summarizes the conclusions and future works.

II. Related Work

In this section, we are going to compare other techniques utilized to detect weed in different crops.

The detection of weeds is an important issue for agriculture. Therefore, many scientists have been working on their identification based on images. The use of drones has increased the possibilities, and in recent years several papers have been published.

The use of image processing to determine the presence of weeds in maize fields was presented by Burgos-Artizzu et al. in 2011 [12]. They described a computer vision system that can be used with videos. They tested their system under different light conditions. The system detected 95% of the weeds and 80% of the crops.

Paikekari et al. presented in 2016 [13] an image processing methodology for weed detection. First, they used color to differentiate soil and grass. Then, the resultant image was converted into a greyscale image to apply an edge detection technique. Finally, the resultant image of edge detection was divided into 25 blocks. The analysis of each block determined if it contained weed with narrow leaves, weed with wide leaves, or crop.

In 2018, Gao et al. [14] presented the use of aerial images with an ultra-high-resolution to detect intra and inter-row weed. They used a semi-automatic object-based image analysis with random forests. In addition, they used techniques to classify soil, weed, and crop. The authors applied this proposal to maize crop fields. The utilized images show the maize in the first days of growth. Their results have a coefficient of correlation of 0.895 and a mean squared error of 0.026.

Marín et al. in 2017 applied simple image processing techniques in different publications to detect the grass coverage in lawns [15][16]. They worked with the histograms of the grass images to determine the weight of the grass and the level of coverage (high, low, very low).

On the other hand, there are other types of studies focused on identifying different leaf affections. One example is the work developed by Khanaa and Thooyamani in 2017 [17]. They proposed an algorithm based on image processing. Their algorithm was able to detect different leaf diseases, such as bacterial pith necrosis, early blight, white trail, and target spot among others.

Finally, Parra et al. in 2019 [1] showed the use of a new form of weed detection based on photographs taken from drones. In their article, they used the combination of pixel values in the three bands (RGB) to differentiate different types of surfaces (soil, grass, and weeds). Their results were promising and offer different types of formulas depending on the needs with different percentages of false positives (FP) and false negatives (FN).

III. Proposal

In this section, we are going to detail the proposed system for lawn monitoring. The system is composed of a drone that flies over the lawn and takes photos. Then, the images are evaluated to determine where there are weeds in the lawn to program the application of phytosanitary products.

A. *Drone*

Our system uses a drone to take images of the lawn. Since we need a spatial resolution of 1mm we should select a drone with a camera that has a high spatial resolution and flies at high height altitude. Nevertheless, we can select a drone with a camera that presents lower spatial resolution and flies at a lower height. In order to calculate the flying height according to the camera resolution, we can use the equations proposed by Marin et al. [16]. We are going to use an Arduino camera with 640X480 pixels, and the flying height will be 2.3m.

It is important to note that for our proposal we are going to use a drone with no camera. We will add the above-mentioned camera connected to a Raspberry Pi 3 node. The Raspberry Pi 3 node will be in charge of taking images and analyzing them. Nonetheless, the flying issues will be operated by the drone processor, not by the Raspberry Pi 3 node. Thus, we can split the task into different processors and our system can be adaptive to different situations.

B. *Operational principle*

Once the images will be gathered by the camera installed on the drone, the same node will analyze them. We need a fast analysis because the processor should analyze the data during the flight in order to trigger the sprinklers of the phytosanitary products. Thus, it is necessary to focus on simple image processing techniques and use a node with high processing capacity. Therefore, we propose to use a Raspberry 3 to analyze the data.

Furthermore, we reduce our possibilities to the operations that involve only the RGB data of each pixel in the image. Therefore, we will avoid image recognition techniques. This type of technique, image recognition, offers accurate results. Nonetheless, they require higher processing capabilities and internet connection in some cases. On the other hand, the methods that use only the pixel values are common when we work with satellite images, which are multispectral images.

Our challenge is to detect weeds in the lawns with the combination of only three image bands, red, green and blue (RGB). We can use two different options for detecting the weeds, the first option is the mathematical combination of the pixel values of the bands. Thus, operating with the pixel values of the RGB bands we can obtain a new image composed of pixels, whose values are a linear combination of the previous bands. Due to the fact that the soil, grass, and wild species have different coloration, this is a feasible option to differentiate the three surfaces.

The second option is to use a combination of the pixel value and their neighbors from a single band. There are several techniques that use this method and are known as edge detection. It is important to note that the edge detection techniques are applied to one of the RGB bands. Therefore, they work with images in black and white. Edge detection techniques include different mathematical methods aimed to identify points in an image at which the brightness changes sharply. Since the aspect of grass and wild species are different, they will generate different patterns of brightness changes. The grass is composed of small and sharp leaves while most of the wild species have wide leaves. Therefore, the areas covered by grass will present more changes than the areas covered by wild species.

The proposed system is shown in Figure 1, we can see the different bands obtained and their names. The red, green and blue bands of the image are also known as band 1, band 2 and band 3.

C. Studied lawns

The proposed system was tested in Finca El Encin, research facilities of the Instituto Madrileño de Investigación y Desarrollo Rural, Agrario y Alimentario (IMIDRA) in Spain. There are small experimental plots where other scientists are testing multiple grass combinations. During their research, different weeds appear in their lawns. We use their experimental plots to take images of different types of lawns with and without the presence of weeds.

By using these experimental plots, we ensure that we will have lawns with different types of grass and under different environmental conditions. The plots used in the first step can be seen in Figure 2.

In order to have verification, other images were taken in a different scenario. These images were gathered in Gandia, Valencia (Spain) in the gardens of Universitat Politécnica de Valencia (UPV). We intend to have a combination of images with and without the presence of grasses to test the system performance in terms of FP, FN, true negatives (TN) and true positives (TP).

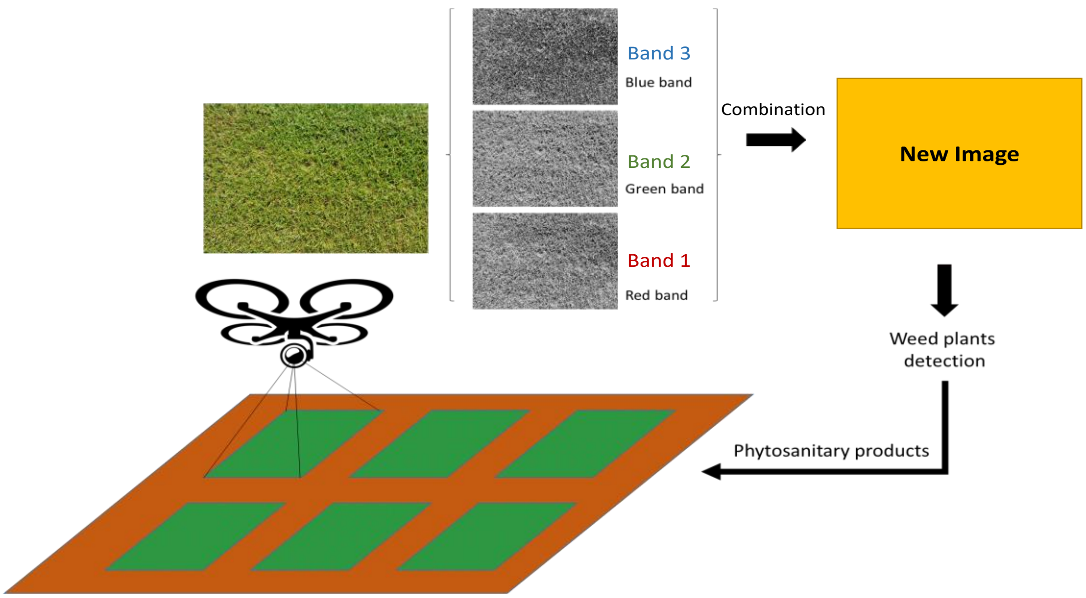


Figure 1. System description.

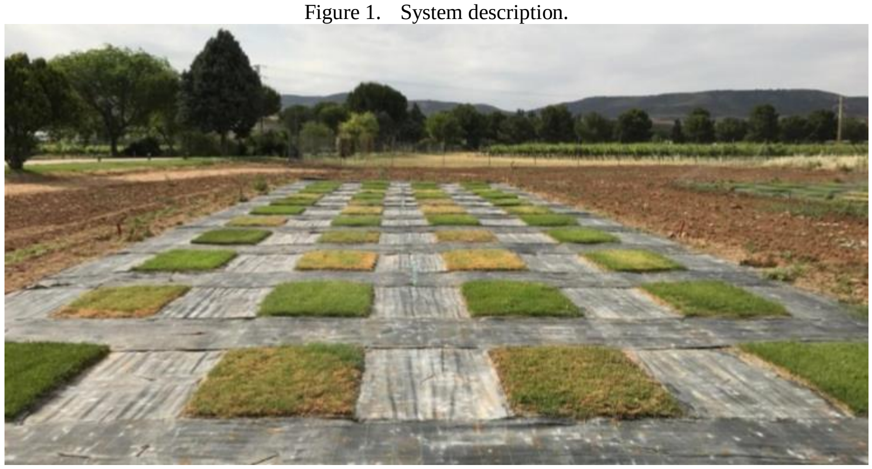


Figure 2. Lawns image

Moreover, we include images with different illumination conditions and with shadow areas to evaluate the possible negative effects. The characteristics of the used cameras are summarized in Table I.

IV. METHODOLOGY

In this section, the methodology for the image analyses is described. First, we describe the operations applied before the use of the proposed techniques, also known as pre-processing. Following, the technique of RGB combination is described. Subsequently, the edge detection techniques are detailed. Finally, post-processing is established.

A. Image pre-processing

In this subsection, the steps for image pre-processing are described in detail. The first step is the clipping of the image. The aim of this step is to ensure that all the pixels of the image are representing grass. This step is only used in the tests for evaluating the techniques. In the used images there are some external objects like architectonic elements (streets, park benches, and tarpaulins). Once the techniques are used in the real system, the gathered images will be only taken in the grass area of the garden and no other architectonic elements will appear. Therefore, this step is performed manually.

The next step is to extract from the image the areas covered by dead grass or soil (areas of the garden without grass coverage). The objective is to avoid FP in the areas of soil. This is especially important in the case of edge detection. For this purpose, we are going to use the linear combination of RGB values of the pixels to differentiate the areas covered by healthy grass from the areas covered by soil or dead grass.

As a result, we will obtain an image that solely contains the areas covered by healthy plants (grass or weed species). Now, the obtained image is ready for being processed.

B. Image processing: RGB combination

In this subsection, the details of the RGB combination for detecting the presence of weeds are described.

The first issue to be considered is that it is not possible to work with threshold values of only one of the layers. Because these values are greatly affected by sun exposure, the presence of clouds, and even the day of the year. Thus, we need to work with a mathematical combination of different bands to avoid this problem.

The second issue is related to the values of the pixels. Each pixel has a value between 0 and 255 in each one of the bands. The value is directly related to the brightness of the pixels. The pixels with higher values are represented in lighter colors. Meanwhile, the pixels with low values are displayed in darker colors. The areas with green color will have high values in the bands of green and lower values in the blue and red bands.

The value of the pixel has no decimals and can only have a positive value. When we are applying the mathematical combinations, these rules are maintained. The resultant value of each pixel will be a positive value with no decimals. When mathematical operations are used, the maximum value can exceed the value of 255.

The objective of this step is to obtain a new image where the values of pixels belonging to grass coverage are different from the values of pixels belonging to weed coverage. Therefore, we will explore the differences in the values of weed and grass in each band and find a simple mathematical expression that maximizes these differences in the resultant bitmap image. We will use different mathematical combinations of the bands to obtain a new image with low values in the areas covered by grass and high values in the areas covered by weeds.

C. Image processing: Edge detection

In this subsection, the information of the edge detection methodologies is described. There are many techniques for edge detection and we are going to describe the basics of the used ones.

All the used filters can be used individually, but some of them offer better results when they are combined. For example, the gradient filters or the line detection filters. In this case, the four available filters are used individually. Then, the resultant image of each filter is combined (by adding the values of the individual images) having, as a result, a new image.

The most important thing to know is the fact that these tools help us find the points of the photograph where there is a change in pixel values. Generally, these zones represent the edges of an object or, in our case, of a leaf. To detect this change, a mathematical operation is performed with the value of the pixel and its closest pixel, called neighbors. The operation to be performed will depend on the specific tool, or filter, used. Most of them use the value of that pixel (PI) and its 8 nearest neighbors (N1, N2, ..., N8) for the calculation of the new value assigned to this pixel, forming a 3x3 matrix, as can be seen in Figure 3.

TABLE I. CHARACTERISTICS OF UTILIZED CAMERAS

Characteristics	Images in IMIDRA	Images in Gandía
Size of the image	2048x1536 pixels	4032x3024 pixels
Horizontal and vertical resolution	72 ppp	72 ppp
Bit Depth	24	24
F point	f/7.1	f/1.7
Focal distance	5mm	4mm
Exposure time	1/400 s	1/100 s
ISO Velocity	ISO - 125	ISO - 80

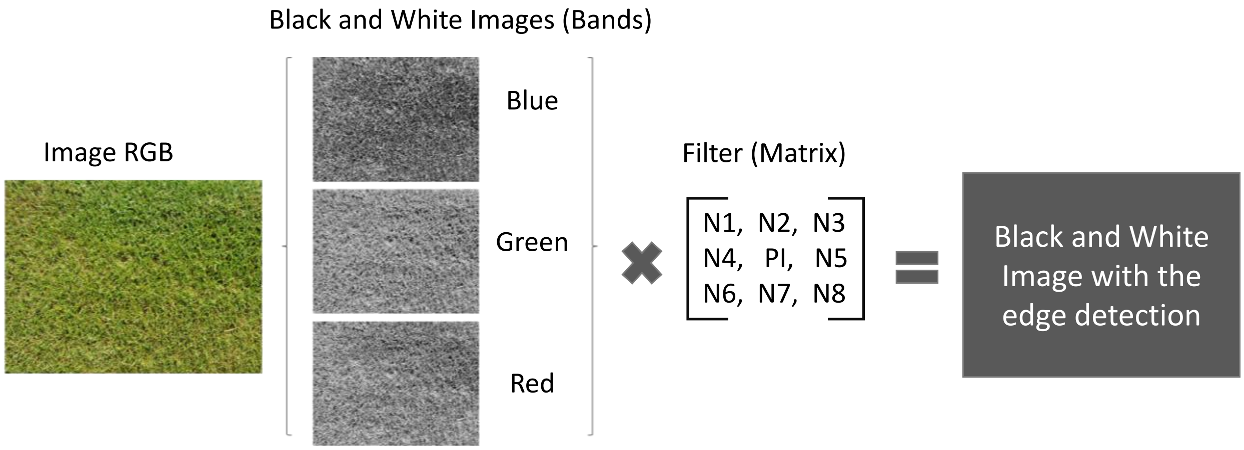


Figure 3. Use of filters in the image

Whichever filter is used, the result will be a new image in black and white where pixels that are not edges will have very low values, close to 0. Meanwhile, pixels that represent a zone of change, which is an edge, will have high values. There is no maximum value, the values will be higher or lower depending on the filter used. Our goal will be to find the areas of the image that have very low values. In the images taken, the areas covered by grass have numerous edges, while the areas where there are weeds are areas with greater uniformity in the pixels. Therefore, the areas with low values after the application of filters will represent the areas with weeds. Following, we detail the filters that have been used in this study.

First, there are the edge detection filters, among which we find: the gradient filters, Laplacian filter, line detection filters, and Sobel filter. There are other edge detection filters but those are the ones we are going to use in the study.

Gradient filters are the best when we want to detect edges in increments of 45º. Based on this type of filter we find the north, east, south, and west gradient filters.

Secondly, we will use the Laplacian type filters. We will use only one of the variants, the one which uses a 3x3 matrix. This filter is useful for detecting edges, whatever the orientation of the edge. The Laplacian filter is recommended for the enhancement of linear features, especially in urban environments.

The next filter used is the line detection filter, very similar to the gradient filter. There are four variants of this filter, according to the direction in which the edges are highlighted, vertical line, horizontal line, left diagonal line and right diagonal line.

The last type of edge detection filter is the Sobel filter. Since the matrices used by these filters are identical to some used in gradient filters, Sobel filters are not included. All edge detection filters use a 3x3 matrix as can be seen in Figure 4.

On the other side, there are the sharpening and smoothing filters. In our case, we will use only those of sharpening. The smoothing filters will be used later on for other purposes. The sharpening filters are recommended to be used so as to highlight the comparative difference of values with their neighbors. They allow us to enhance the boundaries between objects in the photographs. In this case, and despite the existence of other filters in our study, we have included only three of them: two filters that use a 3x3 matrix and a 5x5 matrix, which can be seen in Figure 5.

D. *Post-processing*

Finally, to ensure the selected areas belong to wide leaves of weeds and minimize the FP, we apply an aggregation technique. These techniques are described in this subsection.

Aggregation techniques allow, first of all, the combination of the value of a pixel and its neighbors, resulting in a new pixel; and secondly, increasing the size of the new pixel. The value of the new pixel, as well as its size compared to the previous pixels, will depend on the technique we use. There are different types of aggregation techniques. We can use different types of mathematical operators, such as maximum, minimum, median, mean, or even summation. Then, the size of the cell must be defined. The bigger the cell is, the higher the number of pixels will be used for the mathematical operator. Thus, the resultant pixels will be bigger than if we select a small cell.

In the case of the RGB combination, the objective is to find a group of pixels with high values and avoid FP due to an isolated pixel with high value. Those isolated pixels with different values are generally related to light sparkles in the leaves of grass or due to errors in the image. As this type of pixels usually appears isolated, the possibles FPs are easily corrected with the aggregation technique, since their neighbors have regular values (belonging to grass or to weeds). Therefore, to detect the presence of a group of pixels with high value we will use as aggregation technique the mathematical operator of minimum, mean and median. Thus, if an isolated pixel has a high value (without belonging to weeds), once the mathematical operation is performed the resultant value will be lower due to the low values of its neighbors. However, when a group of pixels (belonging to weed leaves) have a high value, when the mathematical operation is done the resultant pixel will have a high value. We will test as aggregation cell value the sizes of 3, 5 and 10.

In the case of edge detection, we seek to identify areas that have a group of pixels with low values. Thus, we will use the sum of all the pixels and the maximum value of the included pixels as an operation to calculate the value of the new pixel. As for the resulting pixel size, or cell size, we use the values of 3, 5 and 10.

With the obtained image from the aggregation technique, threshold values must be taken to differentiate the pixels we consider positive (weeds) and negative (grass). There are different techniques to do it. In previous papers, the one which has shown a better result in changing lighting conditions has been the creation of classes based on statistical parameters. This option offered better results than taking a threshold value and applying them to all cases as was done in [10].

To sum up the whole process we have created a block diagram that represents all the steps carried out in this paper. The part of pre-processing is not included. The flow is presented in Figure 6.

North Gradient

$$\begin{bmatrix} -1, & -2, & -1, \\ 0, & 0, & 0, \\ 1, & 2, & 1, \end{bmatrix}$$

East Gradient

$$\begin{bmatrix} 1, & 0, & -1, \\ 2, & 0, & -2, \\ 1. & 0. & -1, \end{bmatrix}$$

South Gradient

$$\begin{bmatrix} 1, & 2, & 1, \\ 0, & 0, & 0, \\ -1. & -2. & -1, \end{bmatrix}$$

West Gradient

$$\begin{bmatrix} -1, & 0, & 1, \\ -2, & 0, & 2, \\ -1. & 0. & 1, \end{bmatrix}$$

Laplacian

$$\begin{bmatrix} 0, & -1, & 0, \\ -1, & 4, & -1, \\ 0. & -1. & 0, \end{bmatrix}$$

Vertical Line

$$\begin{bmatrix} -1, & -1, & -1, \\ 2, & 2, & 2, \\ -1. & -1. & -1, \end{bmatrix}$$

Horizontal Line

$$\begin{bmatrix} -1, & 2, & -1, \\ -1, & 2, & -1, \\ -1. & 2. & -1, \end{bmatrix}$$

Left Diagonal Line

$$\begin{bmatrix} -1, & -1, & 2, \\ -1, & 2, & -1, \\ 2. & -1. & -1, \end{bmatrix}$$

Right Diagonal Line

$$\begin{bmatrix} 2, & -1, & -1, \\ -1, & 2, & -1, \\ -1. & -1. & 2, \end{bmatrix}$$

Figure 4. Used edge detection filters

Increase Sharpness

$$\begin{bmatrix} -0{,}25, & -0{,}25, & -0{,}25, \\ -0{,}25, & 3, & -0{,}25, \\ -0{,}25. & -0{,}25. & -0{,}25, \end{bmatrix}$$

Sharpness [3x3]

$$\begin{bmatrix} -1, & -1, & -1, \\ -1, & 9, & -1, \\ -1. & -1. & -1, \end{bmatrix}$$

Sharpness [5x5]

$$\begin{bmatrix} -1, & -3, & -4, & -3, & -1, \\ -3, & 0, & 6, & 0, & -3, \\ -4, & 6, & 21, & 6, & -4, \\ -3, & 0, & 6, & 0, & -3, \\ -1, & -3, & -4, & -3, & -1, \end{bmatrix}$$

Figure 5. Used sharpening filters

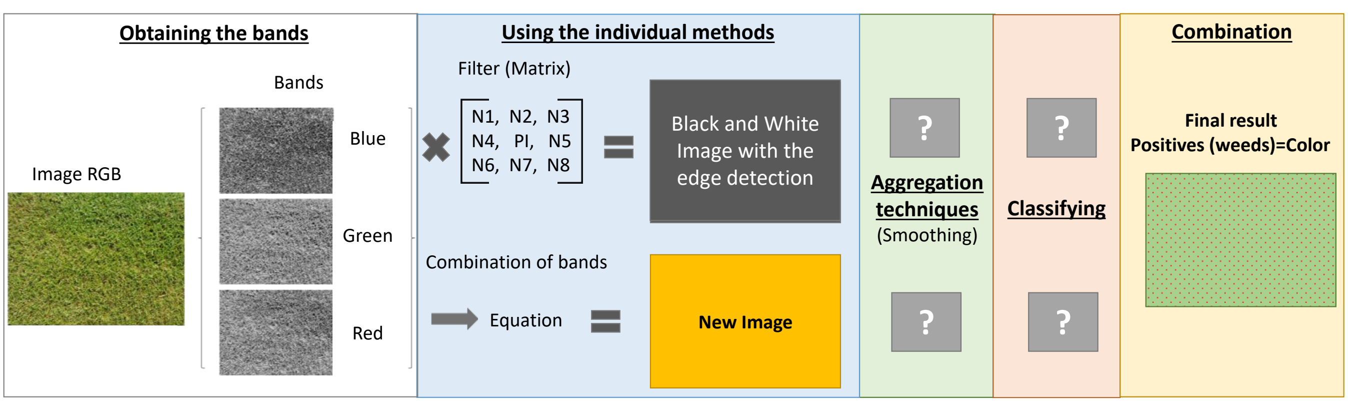


Figure 6. Block diagram of the followed steps

To evaluate the performance of the proposed methodology we will use the following parameters: (i) FN: we will consider how many weeds have not been indicated by any pixel after the analysis. (ii) FP: will be given as the total pixels that, according to the methodology used, indicate the presence of weeds although it is grass. (iii) TP: will be considered as the number of weeds that are indicated by one or more pixels.

V. RESULTS

In this section, we are going to show the obtained images and its processing to determine the presence or absence of weeds. First, we show the process to obtain the equations to detect the weed. Finally, we will present its verification.

A. *Image pre-processing: soil removal*

The image processing method is shown in this subsection. First, Figure 7 presents the RGB images in four different cases. The first one is a lawn with low grass coverage and with the presence of weeds at the top-center part. The weed has a darker coloration than the grass. Furthermore, it presents higher relative values in the blue band, compared with the rest of the grass. Image 2 is taken in a lawn with high grass coverage. There is a weed at the bottom-left of the image. As in the previous case, the weed has a more bluish coloration.

In Image 3, we can see a lawn with low grass coverage and with the presence of the weed in the bottom-right of the image. In this case, the weed has a more yellowish coloration, compared with the grass. Finally, Image 4 represents typical lawns with no weeds; but, under light water stress. Thus, there are some parts of the grass that have a yellowish coloration due to the lack of water.

The first issue that we can pay attention to is the fact that the soil has higher values of brightness in the red band than in the green band. Therefore, considering that the values of the pixels only can be positive and without decimals, we divide the green band by the red band obtaining a new image, which gives us information about the soil/plant coverage, see (1). The result of this mathematical relation between bands can be seen in Figure 6. The grass pixels have values higher than zero and are colored in green. The soil pixels have values of zero and are colored in yellow. Unfortunately, the portions of grass that have suffered from stress or have been strongly compacted, present a similar coloration than the soil. Consequently, those portions might be classified as soil. For our application, it is not a problem, because the important part for us is the green grass and green weeds.

$$Soil\ removal = {}^{Band\ 2}/_{Band\ 1} \qquad (1)$$

B. *Image processing: weed recognition with RGB combination*

The next step is to find a mathematical relation, which gives, as a result, a new image with different values for pixels of grass and pixels of weed.

We have two different types of weed, the ones with more bluish color, and the ones with more yellowish color than the grass. Consequently, we will need two different equations to detect the presence of weeds. One equation for the bluish weed, the ones which appear in RGB Image 1 and RGB Image 2 of Figure 7. Another equation for yellowish weed, like the one which appears in RGB Image 3 of Figure 7, will be needed. The first equation, (2), will be used to detect the bluish weed. This resultant image after applying (2) will have high pixel values where there is a bluish weed. Thus, the equation has to maximize the data of pixels with higher relative blue values. Then, the data from the blue band should be divided by the data from the red and green bands. Since the dividend of the equation (blue brightness value of the pixel) has lower values than the divisor (green x red brightness values of pixels), and the pixels can only be a natural number, almost all the pixels have a value of zero.

Thus, no differences were found. In order to increase the value of the dividend, we square it. Nevertheless, the value of the dividend is still lower than the value of the divisor in the majority of the cases and most of the pixels have a value of zero in the resultant image. Finally, we cube the divisor. Then, we obtain a new image with different values for different coverage surfaces. The obtained image combination that is used to detect bluish weeds can be seen in (2).

On the other hand, we have an image with yellowish weeds. To detect them we should use the opposite steps than in the preceding paragraph, we have to use the data from green and red bands for the dividend and the data from the blue band for the divisor. As in this case, the values of the dividend are always higher than the values of the divisor, it is not necessary to neither square nor cube any of them. Therefore, the proposed formula, which can be used to detect the yellowish weed, is given by (3).

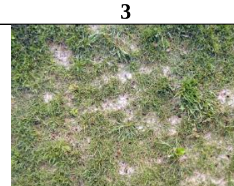
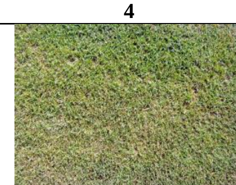
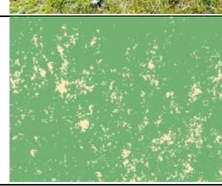
Image nº	**1**	**2**	**3**	**4**
RGB image				
Soil/Grass Coverage				

Figure 7. Images utilized to obtain equations for weed detection

$$Weed = \left({Band\ 3^3}/{Band\ 2} \times Band\ 1 \right) \quad (2)$$

$$Weed = \left({Band\ 2 \times Band\ 1}/{Band\ 3} \right) \quad (3)$$

The result of applying (2) and (3) to the RGB images of Figure 7 can be seen in Figure 8. We apply both formulas to all of the images to show the effectiveness of each formula for generating a new image that contains information about weed presence. The different colors represent different values in the image. The pixels with yellow tones have lower pixel values. On the contrary, the pixels with purple and blue colors have the highest values. In the RGB image, the presence of weed and its position are indicated with red circles.

As it is expected, the pixels that contain bluish weeds (RGB Image 1 and RGB Image 2 in Figure 8), present higher values in the resultant image after applying (2) than the pixels that contain grass or soil. The pixels of the resultant image that have higher brightness values are represented in purple and blue colors. Meanwhile, the pixels with low brightness values are colored in yellow and light yellow. We can see that Image 1 and the resultant image of (2) present higher pixel values, colored in blue, in the area where there are weeds. The resultant image of (3) presents higher values in the pixels that represent one of the grass species in Image 1. In Image 2, there is no specific area that contains pixels with high values.

For Image 3, we can see that the pixels of the image obtained with (2), which have the highest values, are not related to the presence of weeds. However, in the image obtained with (3), we can clearly identify the presence of the weed. We can see that one of the grass species present in the lawn of Image 3 is giving high values (red color). But the purple and blue colors are only related to the weed presence.

Finally, the resultant image of the image from the lawns without weed does not present any areas with high values. In the case of the resultant image of (2), there are some pixels with high values. Nevertheless, they appear scattered around the image, not joined in one area as in the other cases. Meanwhile, in the image of (3) almost all the pixels present low values and few pixels have high values.

As the higher values indicate the presence of weeds, to evaluate the aggregation technique we are only going to consider the pixels with the highest values. We will use the natural breaks, jenks, to divide the pixels into 5 groups and only the last group will indicate the presence of weeds.

One of the major advantages of the proposed system is that its results should not be affected by changes in solar exposition. Thus, we are going to test the aggregation technique with images gathered at another time period with different environmental conditions. Moreover, we are going to evaluate the use of a smoothing technique to reduce FP.

The used images and the results of the analysis of the aggregation technique can be seen in Figure 9. Again, the position of weed is marked with a red circle in the RGB image.

Image 5 of Figure 9 was gathered on a sunny day and represents a lawn with low grass coverage, with two types of soil (light and dark brown), and with the presence of a lot of weeds. Some of the weeds of Image 5 of Figure 9 are a bluish weed, then, the results are after applying (2). Image 6 of Figure 9 was taken on a day with less solar radiation. The image represents a lawn with some grass patches and the presence of yellowish weed at the bottom of the image. Therefore, the verification is done with (3). Finally, Image 7 of Figure 9 represents a lawn with regular grass coverage on a cloudy day. In Image 7 of Figure 9, no weeds are present, the results are obtained with (2). We select (2) because it is the one that gives more FP in the previous test. The results with the cell value of 10 have not been presented, because they were not representative. We are going to present the results of a cell value of 5.

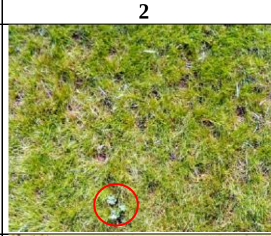
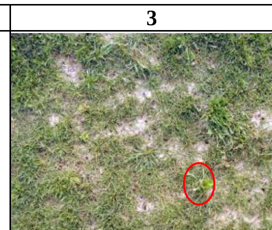
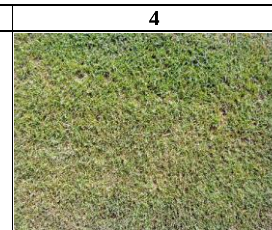
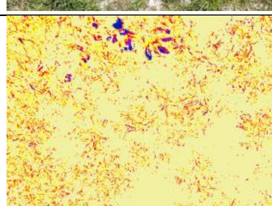
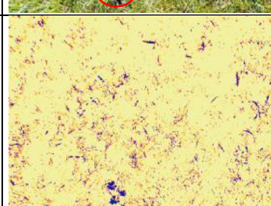
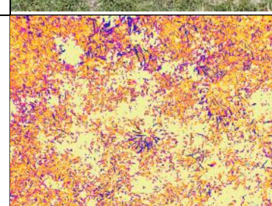
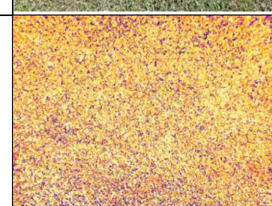
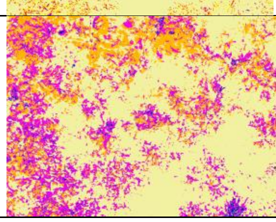
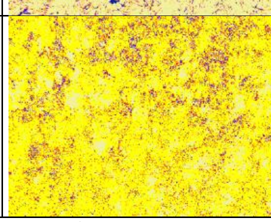
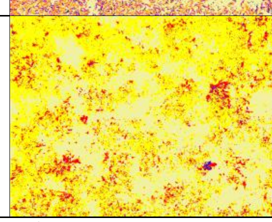
Image nº	1	2	3	4
RGB image				
Result of apply (2)				
Result of apply (3)				

Figure 8. Images Obtained After Apply The Formulas Of (2) and (3) For Weed Detection

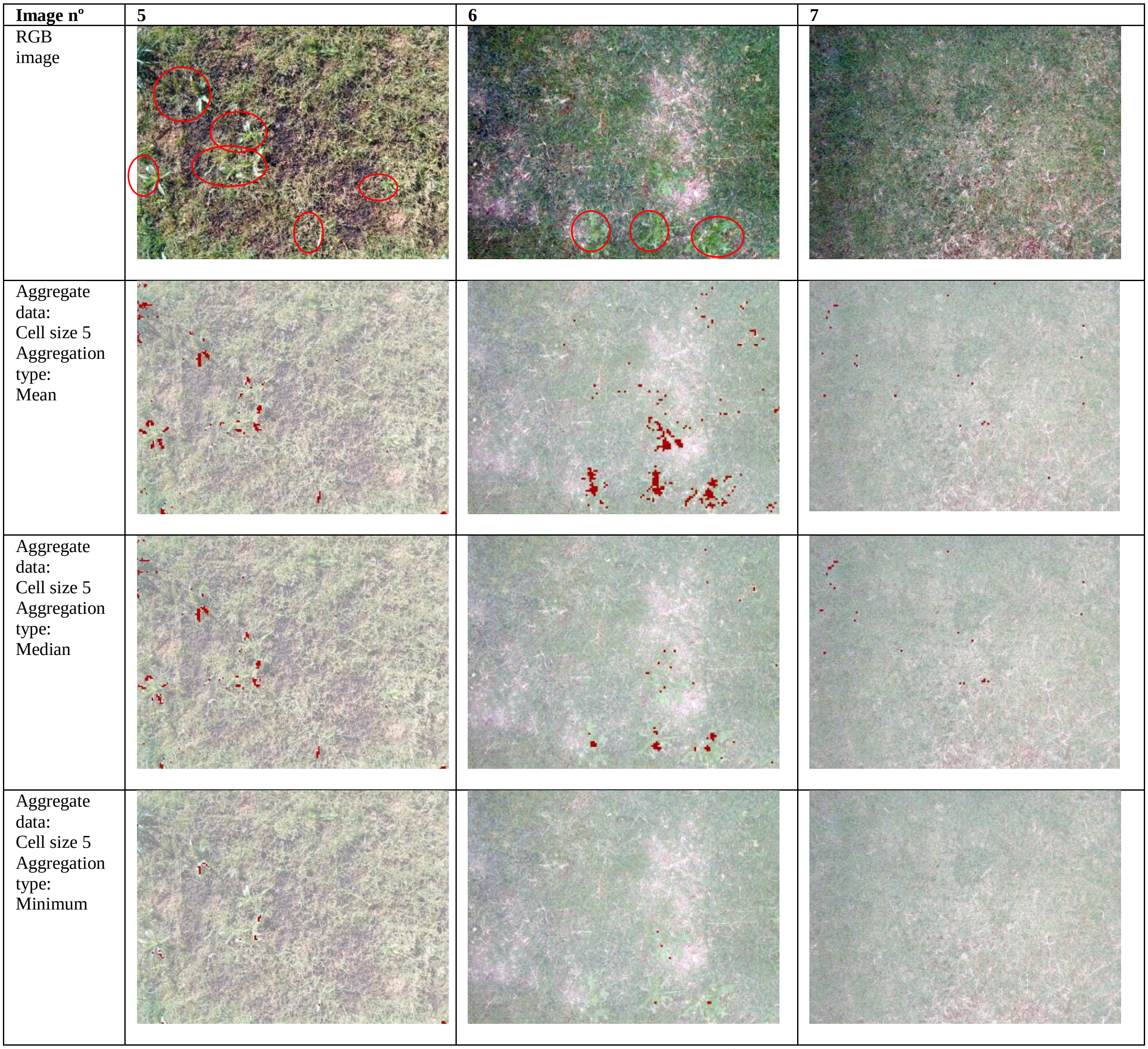


Figure 9. Original images and obtained images in the verification process

First, we present the results of the aggregation technique, which uses the mean as a result. This technique is quite accurate in terms of identifying the leaves of the weeds. However, there are still some FP, which identify as a weed normal grass leaves, FP= 12, >40 and 22 in Images 5, 6 and 7. The FPs are more visible in the case of Image 7, where there was no weed. The number of FN is very low, FN= 1, 0 and 0 in Images 5 to 7. Finally, the number of TP is considerably high compared with the FN, TP= 5 out of 6, 4 out of 4 and 0 out of 0 in Images 5 to 7.

The results of using an aggregation technique with the median have less FP (FP=9, 11 and 21 in Images 5 to 7). In terms of FN and TP, the results of using the median value are the same as those of using the mean value.

Finally, if we use the minimum as a mathematical operator, the results show that FP=0 in all the images. Nevertheless, by utilizing this technique we have some FN (FN=3, 1 and 0 in Image 5, Image 6, and Image 7 of Figure 8).

Thus, depending on the application and the produced effects on the case of FP and FN, we can use one aggregation technique or other. For our application, since the objective is to maximize the grass quality by minimizing the phytosanitary products usage, we prefer to have FP than FN. Therefore, we propose to use the aggregation technique that uses the median as a result.

C. Image processing: weed recognition with edge detection

The results of applying the filters described in Figures 4 and 5 are detailed in these paragraphs. To set-up of the system we have used different images, see Figure 10. The images were taken at the same height, some of them represent gardens with grass. Furthermore, we include an image, Image 4 in Figure 8 and Figure 10, which contains grass and weeds.

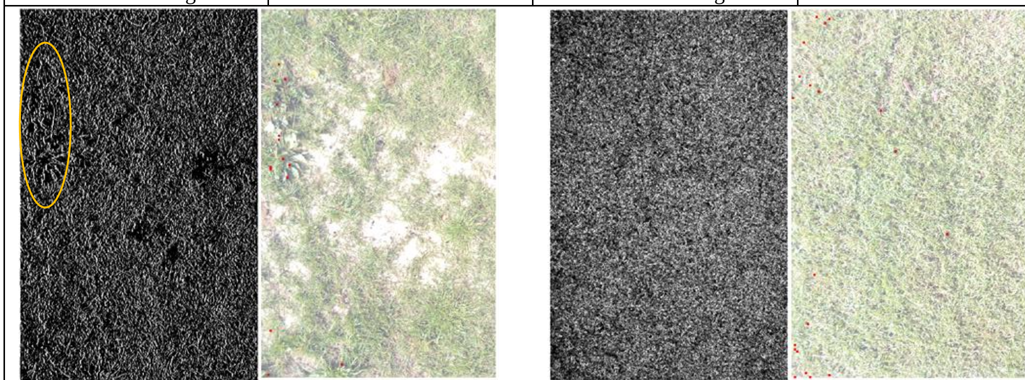
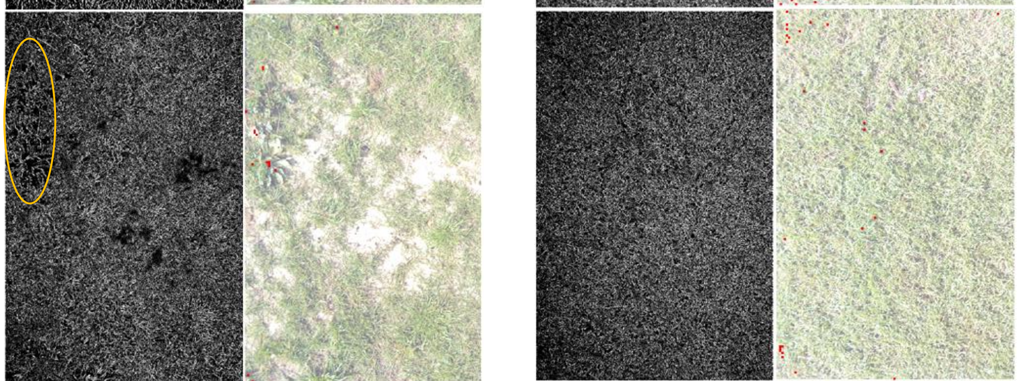
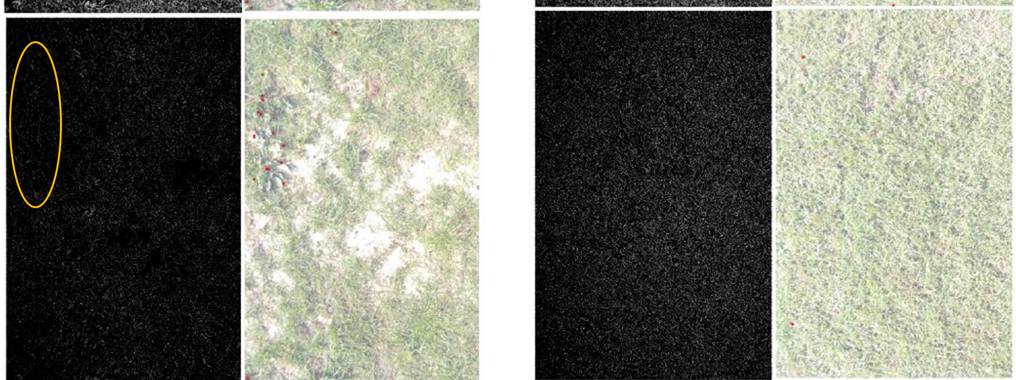
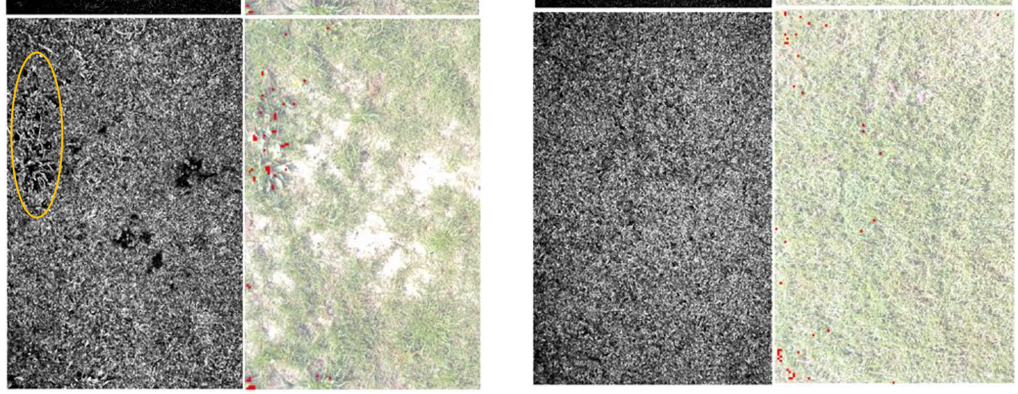
Image with weeds (Image 1 in Figure 9)		**Images without weeds(Image 4 in Figure 9)**		**Method**
Resultant image	Weed detection	Resultant image	Weed detection	
				A)
				B)
				C)
				D)

Figure 10. Image obtained after edge detection filters

We analyze the effectiveness of each filter presented in the previous section and the best results are shown. First, the best aggregation technique for all cases has been the sum with a cell size equal to 5. It has also been observed that there are no differences in the results when the filters are applied to the different bands (RGB) of the image. Therefore, the results shown in this section correspond to the use of the filters in the red band. The presence of weeds in Figure 10 is indicated with yellow circles.

Gradient filters, when used individually, have given very bad results. Despite applying aggregation techniques, the results did not clearly indicate the presence of weeds. However, when all the gradient filters are used together (each one applied separately and adding the 4 images obtained), the results markedly improve, see Figure 10 method A. The same behavior has been found with the line detection filters, by adding the images from the individual filters the results improve considerably (Figure 10 Method B).

In both cases, the presence of dicotyledonous weeds has been detected. In the case of the line detection filter, a monocotyledonous weed has been detected in the image with weeds (TPs = 4 in both cases). Conversely, in both cases, two of the weeds have not been detected, FNs = 2. Therefore, we have FNs, which would cause the non-detection of a wild plant. There is no case FP in the image with weeds. Regarding the image without weeds, both filters give a considerably high number of FPs, 20 with method A and 24 with method B.

In relation to the Laplacian filter (Method C in Figure 10), it has offered very good results without the need to be combined with other filters. Laplacian filter is the one that generates less FP when there are no weeds, FP = 2. In the case of the image with weeds, the results are equal to the previous filters, it has detected 4 out of the 6 plants, TP = 4 FN = 2.

Finally, the sum of the gradient filters plus the line detection filters has a great capacity to detect weeds (Figure 10 Method D). In the photograph with weeds, it is able to detect the presence of all of them, therefore it results in TP = 6. However, in this photograph, the combination of filters indicates the presence of weeds where there is no weed in two cases, FP=2, both of them located in shadow areas. On the other hand, its result in photographs without wild plants shows that it is the worst option with a total of 39 FP.

The sharpening filters have not given good results in any case, they give a high amount of FP and the TP are not as high as for the edge detection filters. Therefore, these filters have been excluded from the analysis.

It is necessary to consider that up to this point we have worked with the option of classifying the resulting images according to the standard deviation of the image data. However, it has been observed that in this case, the use of a threshold value would be more appropriate. In Table II we present the minimum and maximum values of the class that is considered positive in Image 1 and Image 4 of Figure 10. Therefore, we could propose a threshold value depending on the method like the maximum value of pixels characterized as a weed in the image with weeds and minimum value of pixels characterized as a weed in an image without weed. The following thresholds 75, 100, 18, and 100 are proposed for methods A to D. However, we need to compare the use of threshold values with the standard deviation to classify the pixel values when the light conditions change.

As the methodology that has given the best is C, Laplacian filter, we will check the results when using the threshold value proposed with the previous photographs to other new photographs obtained in Gandía. 3 out of 4 images have been taken in conditions of light similar to the photographs of the previous test (in IMIDRA) and the last one has been taken in conditions of lower light. Images 1, 2 and 4 have weeds, and Image 3 does not.

TABLE II. MAXIMUM AND MINIMUM VALUES OF PIXELS CHARACTERIZED AS WEED

Type of image	Values	Method A)	B)	C)	D)
Image without weeds	Minimum	96	138	19	187
	Maximum	147	214	26	357
Image with weeds	Minimum	0	36	10	36
	Maximum	67	90	19	79

In Table III we can see the results of the comparison of different classification options. In lighting conditions similar to the photographs used to obtain the threshold values, the use of the threshold value improves the results. The amount of FP is reduced in all cases by using the threshold value. The amount of FN has increased in one of the cases, this fact is not as worrying as the FP. We must consider that a FN in an image where the presence of weeds has already been detected has no repercussion since this area will be treated with the phytosanitary anyway. On the other hand, a FP in an image without weeds will cause an area to be treated without any need.

However, analyzing the data in Photography 4, which has been taken in conditions of lower light, we observe that the results of classifying based on the standard deviation are better than the results of the threshold. When classifying with the established threshold value the number of FP is almost 4 times higher. Therefore, threshold values must be generated for different lighting conditions, or use the standard deviation as a classification method.

TABLE III. COMPARISON OF CLASSIFICATION OPTIONS FOR METHOD C

Method	Parameter	Image 1)	2)	3)	4)
Standard deviation	VP	5	8	0	4
	FP	1	≈ 40	2	≈ 60
	FN	2	4	0	0
Threshold value	VP	5	4	0	2
	FP	0	0	1	≈ 200
	FN	0	8	0	2

D. Comparison of both techniques

Finally, we are going to use four new images, two without weed presence and two with weed presence, taken in the same location than images 1-4 to compare the performance of both methodologies.

With regard to the RGB methodology, we will present the most accurate results (from (2) or (3)) using the minimum as aggregation technique, with the objective of having no FP. On the other hand, regarding the edge detection, we are going to present the results using the Laplacian filter with the sum as the aggregation technique and using the threshold value obtained from Table II. A scheme of the combination of methods and techniques is presented in Figure 11. In this Figure, we can see the different steps carried out in order to obtain our results. First, the individual techniques are applied. Following, the aggregation technique is used, followed by the classification method. Finally, both images are joined.

The technique of band combinations offered the following results. The method shows that in both images, the weeds are detected with the (3). The results of this methodology are FP≈45, TP=1, FN=0. In the second image with weed presence, it was not possible to detect the weed presence clearly with any of the RGB methods. With (2) we obtained the following results: FP=5, TP=0, FN=1 and with (3) FP>100, TP=3, FN=0. With the (3) it was possible to detect the presence of weed but the number of FP is very high, and we consider that none of the equations offer appropriated results. Finally, with the images without weed presence, the results of the first and second images are FP=6 and 10 with (2) and FP≈ 100 in both cases with (3).

The results of using the edge detection method are the following ones. In the case of images with weed presence, the resultant images indicate the presence of weed in both cases the weeds are indicated TP= 1 and 3. Nonetheless, the results indicate the presence of weed in areas without a weed in one of the cases FP= 1 and 10. This method does not offer any FN. In the case of images without weed, the method offered in both image results in some FP, FP= 5 and 7 in each image. The resultant images of both filters and their combination in the images with weed presence are presented in Figure 12. First, the original images are shown and the presence of weed is indicated in red circles. Then the individual results of each technique are presented, the positive results (pixels identified as weeds) are in red. Finally, the results of combining both methodologies are presented.

We can affirm that both methods (RGB and edge detection) are promising options for weed detection in grass gardens. Nonetheless, both methods need to be improved since a considerable number of FP are given. This fact is more relevant in the case of the RGB method with (3).

Finally, we can join the data from both methods to improve the actuary. Therefore, if we combine the results of (2) and the Laplacian filter the weed detection improves considerably. The results are summarized in Table IV. The number of FP has been reduced. There is only one FP in Image 2. The importance of the FP in an image when there is a TP, as in the case of Image 2, is low. In the images without weed presence, there is no FP. On the other hand, the weeds are correctly identified in the images with the presence of weed (Image 1 and Image 2). Thus, there is no FN in each image.

VI. CONCLUSION

In this paper, we have presented our proposal for weed detection in lawns using two image processing techniques. The objective is to detect the weeds to apply the phytosanitary products only to the affected area.

We use a mathematical combination of the RGB bands and the edge detection filters to obtain new image data, which can be used to detect the weed. First, we found a formula that can be used to remove the soil from the images as pre-processing. Then, after analyzing the RGB values of the weeds and the grass, we realize that there are two big groups of weeds. The ones with a bluish coloration and the ones with a yellowish coloration, compared with the grass. Thus, we need to use two different formulas to detect the weed. Moreover, several filters for edge detection have been compared and the Laplacian filter was the one that offered better results. Then, we apply aggregation techniques to minimize the number of FP in both methods. Finally, we compare and combine both methods, and observe the improvement of results when both methods are used together.

By using the methodology described in this paper, it will be possible to detect weeds. This methodology is more effective for detecting dicotyledonous weeds, especially the ones with wide and big leaves. Nonetheless, in our results, some monocotyledonous leaves of weeds were detected.

The future work will be related to the identification of different weed species using artificial intelligence and machine learning techniques. Those techniques will be applied not in the node itself, but in a cloud server. Moreover, we will work with images taken at a higher height and evaluate the benefits of using a thermal camera in conjunction with the RGB camera. Finally, and in order to estimate the reduction in phytosanitary product use, we will implement this methodology in golf courses. In those scenarios there is a huge area covered by grass and maintaining them without weeds is a key factor for the manager.

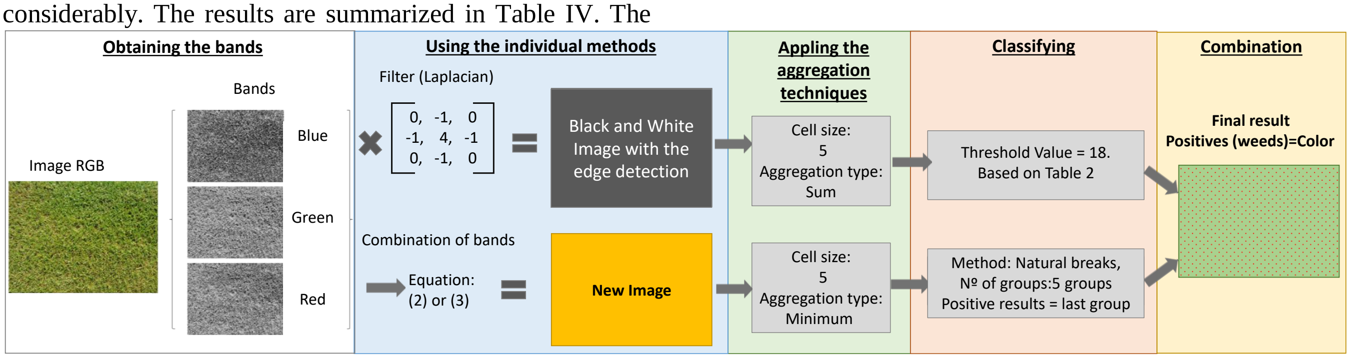


Figure 11. Block diagram of the process including the selected technics.

ACKNOWLEDGMENT

This work is partially found by the Conselleria de Educación, Cultura y Deporte with the Subvenciones para la contratación de personal investigador en fase postdoctoral, grant number APOSTD/2019/04, by European Union through the ERANETMED (Euromediterranean Cooperation through ERANET joint activities and beyond) project ERANETMED3-227 SMARTWATIR, and by the European Union with the “Fondo Europeo Agrícola de Desarrollo Rural (FEADER) – Europa invierte en zonas rurales”, the MAPAMA, and Comunidad de Madrid with the IMIDRA, under the mark of the PDR-CM 2014-2020” project number PDR18-XEROCESPED.

TABLE IV. COMBINATION OF RESULTS

Method	Parameter	Image 1)	2)	3)	4)
Band combination using (3)	TP	1	3	0	0
	FP	≈45	>100	≈ 100	≈ 100
	FN	0	0	0	0
Edge detection Laplacian	TP	1	3	0	0
	FP	1	10	5	7
	FN	0	0	0	0
Combination	TP	1	3	0	0
	FP	0	0	0	0
	FN	0	0	0	0

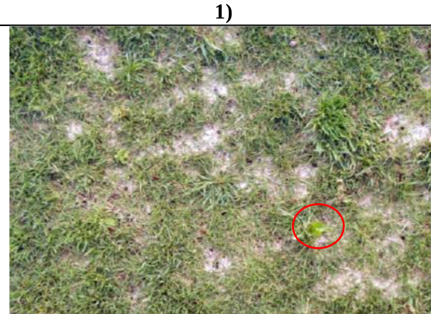
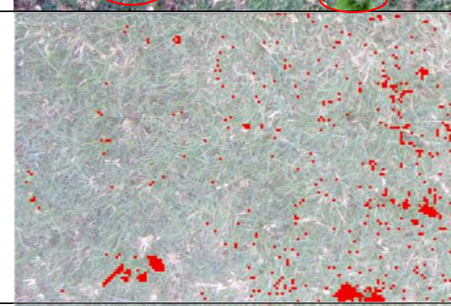
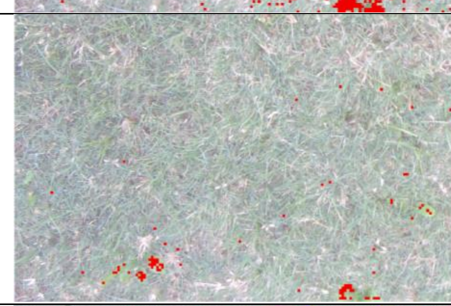
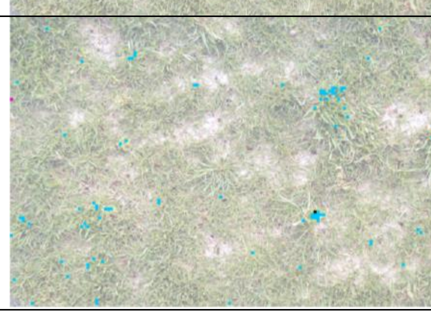
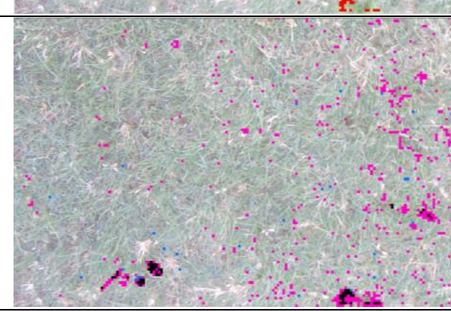
Image	1)	2)
RGB image		
Image of RGB Band Operations using (3)		
Image of Edge detection		
Resultant image of combinations: • **Blue pixels (positive results of RGB)** • **Pink pixels (positive results of edge detection)** • **Black pixels (positive results of combination)**		

Figure 12. Details of the combination of results in Figures with weed presence

REFERENCES

[1] L. Parra, V. Torices, J. Marín, P. V. Mauri, J. Lloret, "The Use of Image Processing Techniques for Detection of Weed in Lawns", The Fourteenth International Conference on Systems (ICONS 2019), Valencia, Spain, 24 – 28 March 2019, pp. 50-55.

[2] M. R. Barnes, K. C. Nelson, A. J. Meyer, E. Watkins, S. A. Bonos, B. P. Horgan, W. A. Meyer, J. Murphy, C. Yue, "Public land managers and sustainable urban vegetation: The case of low-input turfgrasses", Urban forestry & urban greening, 2018, vol. 29, pp. 284-292.

[3] A. Nagase, M. Kurashina, M. Nomura, J. S. MacIvor, " Patterns in urban butterflies and spontaneous plants across a University campus in Japan", The Pan-Pacific Entomologist, 2019, vol. 94, no. 4, pp. 195-215.

[4] Y. H. Hwang, Z. E. Jonathan Yue, "Intended wildness: Utilizing spontaneous growth for biodiverse green spaces in a tropical city", Journal of Landscape Architecture, 2019, vol. 14, no. 1, pp. 54-63.

[5] S. B. Lerman, A. R. Contosta, J. Milam, C. Bang, "To mow or to mow less: Lawn mowing frequency affects bee abundance and diversity in suburban yards", Biological conservation, 2018, vol. 221, pp. 160-174.

[6] R. Roscher, J. Behmann, A. K. Mahlein, J. Dupuis, H. Kuhlmann, L. Plümer, " Detection of Disease Symptoms On Hyperspectral 3D Plant Models. ISPRS Annals of Photogrammetry", Remote Sensing & Spatial Information Sciences, 2016, vol. 3, no. 7.

[7] P. D. Surya and K. J. Satheesh, "Assessment of banana fruit maturity by image processing technique", Journal of food science and technology, 2015, vol. 52, no 3, p. 1316-1327.

[8] D. Li, L. Xu, H. Liu, "Detection of uneaten fish food pellets in underwater images for aquaculture", Aquacultural Engineering, 2017, vol. 78, pp. 85-94.

[9] H. Li, Z. Lin, X. Shen, J. Brandt, and G. Hua, "A convolutional neural network cascade for face detection", Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2015. pp. 5325-5334.

[10] G. Maria, E. Baccaglini, D. Brevi, M. Gavelli, and R. Scopigno, "A drone-based image processing system for car detection in a smart transport infrastructure", Electrotechnical Conference (MELECON), 2016 18th Mediterranean. IEEE, 2016. pp. 1-5.

[11] L. Parra, J. Marín, P. V. Mauri, J. Lloret, V. Torices, A. Massager, "Scatternet Formation Protocol for Environmental Monitoring in a Smart Garden", Network Protocols and Algorithms, 2018, vol. 10, no. 3, pp. 63-84.

[12] X. P. Burgos-Artizzu, A. Ribeiro, M. Guijarro, and G. Pajares, "Real-time image processing for crop/weed discrimination in maize fields", Computers and Electronics in Agriculture, 2011, vol. 75, no 2, pp. 337-346.

[13] A. Paikekari, V. Ghule, R. Meshram, and V. B. Raskar, "Weed detection using image processing", International Research Journal of Engineering and Technology (IRJET), 2016, vol. 3, no 3, pp. 1220-1222

[14] J. Gao, W. Liaob, D. Nuyttensc, P. Lootensd, J. Vangeytec, A. Pižuricab, Y. Hee, J. G. Pietersa, "Fusion of pixel and object-based features for weed mapping using unmanned aerial vehicle imagery", International journal of applied earth observation and geoinformation, 2018, vol. 67, pp. 43-53.

[15] J. F. Marín Peira, , J. Rocher, L. Parra, A. Plaza, P. V. Mauri, J. Ruiz Fernández, S. Sendra, J. Lloret "Automation in the characterization of the cultivation Automatización en la caracterización del cultivo de céspedes en praderas urbanas ", Proccedings of the IX Congresso Ibérico de Agroengenharia, Braganza, Portugal, 4 – 9 Sept. 2017.

[16] J. F. Marín Peira, L. Parra, J. Rocher, S. Sendra, J. Lloret, P. V. Mauri, A. Masaguer, "Urban Lawn Monitoring in Smart City Environments". Journal of Sensors, 2018, vol. 2018.

[17] V. Khanaa and K. P. Thooyamani, "An Efficient Weed and Pest Detection System", Indian Journal of Science and Technology, 2015, vol. 8, no 32.