FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

Vision-based Smart Sprayer for Precision Farming

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Resumo

Hoje em dia, sabe-se que um dos principais temas de discussão é a sustentabilidade. Mudanças climáticas, recursos limitados, e o crescimento populacional nos obrigam a gerenciar melhor nossos métodos agrícolas para reduzir o desperdício de alimentos e a degradação do solo.

Desde o surgimento da agricultura, o homem passou a utilizar produtos químicos para combater as pragas e consequentemente os prejuízos nas lavouras, que, a partir do século XIX, evoluíram para o que hoje conhecemos como agrotóxicos [1]. Porém, esta prática pode danificar o solo, visto que o produto não é aplicado diretamente no alvo. O método de agricultura de precisão usa IA e processamento de imagens para controlar o número de produtos químicos usados em um determinado tipo de planta, reduzindo as perdas e maximizando o uso de recursos. Com base nos estudos anteriores analisados nesta dissertação de mestrado, fica claro que as abordagens mais recentes foram funcionais; no entanto, há potencial para melhorar a precisão, exatidão e aspectos mecânicos do sistema de pulverização. Essas melhorias irão ser compiladas, estudadas, executadas e testadas neste trabalho.

Para atingir o objetivo deste trabalho de dissertação, ou seja, desenvolver um algoritmo funcional para detetar e classificar folhas numa colheita, este trabalho visa:

- Uma revisão sistemática dos algoritmos já existentes hoje;
- Aperfeiçoamento de códigos anteriores, e consequentemente, seus resultados e exatidão;
- Estudar e desenhar uma estrutura para o pulverizador de precisão com dois graus de liberdade;
- Teste e validação do trabalho desenvolvido.

Abstract

Nowadays, it is known that one of the main discussion subjects is sustainability. Climate change, limited resources, and population growth impose us to manage better our agricultural methods to reduce food waste and soil degradation.

Since the emergence of agriculture, humankind started to use chemicals to fight plagues and consequently the losses in the farms, which, from the nineteenth century, evolved into what we know as pesticides today [1]. However, this practice could damage the soil, given that the product is not directly applied to the target. The precision agriculture method uses AI and image processing to control the number of chemicals used in a given type of plant, reducing the losses and maximizing resource usage. Based on the previous studies analyzed in this master thesis, it is clear that the most recent approaches were functional; however, there is potential to improve the sprayer system's precision, accuracy, and mechanical aspects. This work will compile, study, execute, and test these improvements.

To achieve the objective of this dissertation work, that is, developing a functional algorithm to detect and classify leaves in a crop, this work aims to:

- A systematic review of the already existent algorithms today;
- Improvement of the previous codes, and consequently, their results and accuracy;
- Study and design a structure for the precision spray with two degrees of freedom;
- Test and validation of the work developed.

Graphical Abstract

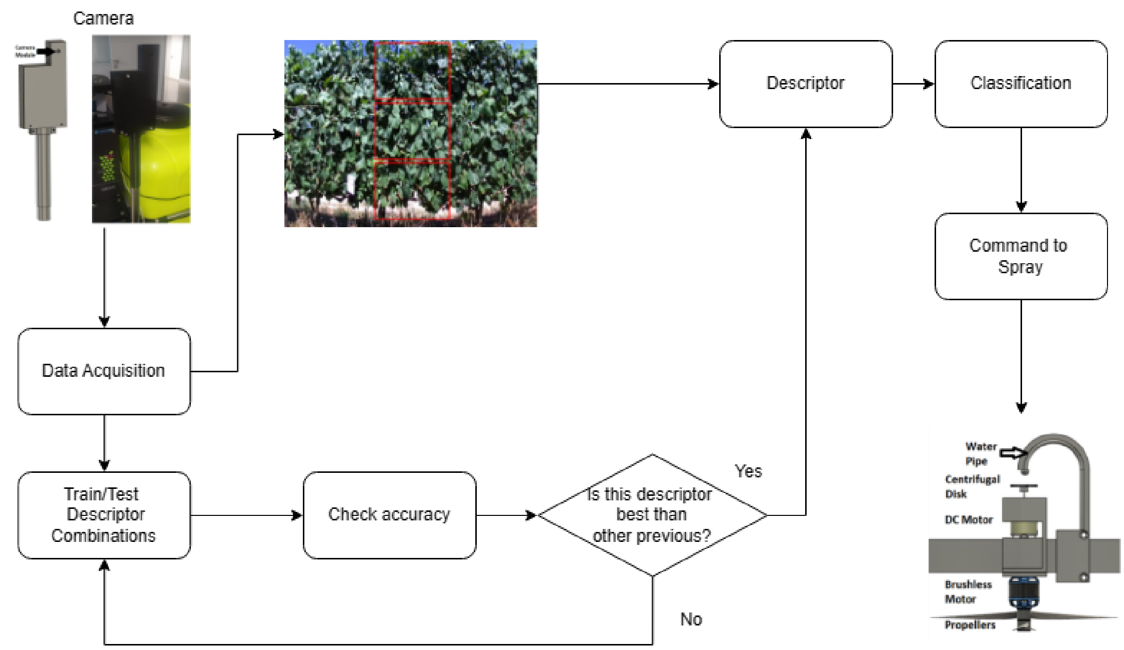

Figure 1: Graphic Abstract, images taken from [2]

Acknowlegments

First, I am very grateful to my advisor, Dr. Filipe Neves dos Santos, for his invaluable advice, continuous support, and patience during the development of the dissertation. His immense knowledge and experience encouraged me throughout my academic research and daily life. I would also like to thank MSc. André Rodrigues Baltazar for always being available to help, remove doubts, and encourage. Furthermore, I would like to express my gratitude to my parents, who allowed me to study and complete my degree at the best university in Portugal, not being afraid to emigrate from Brazil to give better opportunities to our family. Finally, I thank my friends and Tuna de Engenharia at the University of Porto. Without your tremendous understanding and encouragement over the last few years, it would have been impossible for me to complete my studies.

Thaidy Deguchi

"You have to believe in yourself."

Sun Tzu

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Abbreviations and Symbols

AI	Artificial Intelligence
BGR	Blue-Green-Red
CIVE	Colour Index of Vegetation Extraction
DOF	Degrees of Freedom
ExG	Excess Green Index
ExGR	Excess Green minus Excess Red Index
ExR	Excess Red Index
GLI	Green Leaf Index
HSV	Hue-Saturation-Value
IP	Ingress Protection
LPB	Local Binary Pattern
MExG	Modified Excess Green Index
NGRDI	Normalized Green Red Difference Index
NIR	Near-infrared
OpenCV	Open Source Computer Vision Library
PRySM	Precise Robotic Sprayer
PTO	Power take-off
RGB	Reg-Green-Blue
RGBVI	Red-Green-Blue Vegetation Index
RI	Redness Index
ROI	Region of Interest
SLT	Statistical Learning Theory
SVM	Space Vector Machine
VEG	Vegetative Index

Chapter 1

Introduction

1.1 Context

One of the main problems faced today is how to manage the waste of resources. The agricultural process must take advantage of all means possible to maximize production and avoid the losses of pesticides during the spraying activities.

Due to economic and cultural factors and the high demand for food, this research area continues to advance. The precision agriculture method considerably evolved to surpass the availability and conservation of certain fruits in a specific period of the year.

Furthermore, using human labor in the fields is an excellent challenge regarding efficiency and saving resources. Nowadays, spray operations are based on a backpack or air blast sprayers attached to a tiny tractor. These two approaches have several handicaps. Figure 1.1 depicts the various types of sprayers. The manual solution makes it much more difficult to guarantee the quality and quantity of material used by a person than by an autonomous machine. Multiple reasons could be assigned to this, such as distraction, negligence, tiredness, or a lack of workers in the region, problems that are easier to avoid with robots. Due to the off-target spraying and soil compaction issues, the tractor approach makes this solution disadvantageous, with low spraying efficiency [2]. As a result, developing automated robots with vision-based algorithms benefits both the environment and production efficiency.

(a) (b) (c)

Figure 1.1: (a) Manual Sprayer [3] (b) Tractor Sprayer [4] (c) Intelligent Sprayer developed by INESC TEC in 2021 [1]

1.2 Motivation

Inspired by this societal challenge, this work expects to develop an intelligent sprayer capable of covering a larger vegetation area with a single pulverization nozzle by considering a two-degree-of-freedom system. To control the mechanical system will be developed an advanced perception system. This perception system will be capable of detecting the characteristics of the foliage involved and applying the proper dose of pesticide, and after, significantly decreasing the waste of pesticides to the necessary amount, making it less harmful to the environment and the soil. Therefore, this solution aims to mitigate the handicaps presented by the typical approaches today. Besides, this work pretends to improve the previous algorithm and mechanical solutions to raise the project's efficacy. Compiling, studying, and improving the principal solutions in the precision agriculture area today are fundamental steps to achieve this.

1.3 Objectives

The main objective of this dissertation is to develop a precision sprayer capable of covering a larger area of vegetation with just one spray nozzle through movement in two degrees of freedom. It is also intended to detect the characteristics of the surrounding foliage and, depending on it, apply the appropriate dose of pesticide.

To fulfill this objective, the following objectives must be completed:

- Study and design of a structure for a precision sprayer with two degrees of freedom;
- Selection of hardware required for precision sprayer motion control;
- Two-degree-of-freedom precision sprayer motion control;
- Development of a vision-based perception algorithm capable of characterizing the canopy;
- Integration of the perception algorithm in the precision sprayer.

1.4 Contribution

This dissertation provides several contributions to the precision agriculture, robotics, and computer vision area.

First of all, this dissertation does a literature review of the concepts used in this work, such as OpenCV and machine learning. Furthermore, this work aims to test several distinct descriptor combinations to improve previous research. Moreover, there is a literature review of the best mechanical approaches of the sprayer, aiming for the best efficacy with two liberty degrees.

Besides, the conception of a vision-based intelligent sprayer contributes to decreasing the waste of resources and environmental damage.

1.5 Document Structure

The dissertation report is organized into five chapters. Besides chapter 1, chapter 2 presents a background work developed in the last decades. Chapter 3 shows the state of the art. There is a theoretical approach to the different methods to extract descriptors used to train and test the algorithm. The main goal is to present and explain the formulas and their benefits. Moreover, is done a brief review of the hardware. In chapter 4 is presented the preliminary work and work plan. Finally, chapter 5 presents a report's conclusion.

Chapter 2

Background

This chapter illustrates the different approaches to precision farming over the past decades. Also, it is contextualized the pretended improvement idealized by this work.

2.1 Introduction

Over the past decades, researchers tried to improve the precision agriculture technique to surpass the waste of resources. The evolution of this topic is something more and more present in scientific research centers. A simple research in the Scopus database for the query "precision" AND "agriculture" returned more than 16000 articles about this subject. In figure 2.1, it is possible to analyze the growth of published articles from 1990 until 2022. This section compiled the most relevant research to this dissertation work.

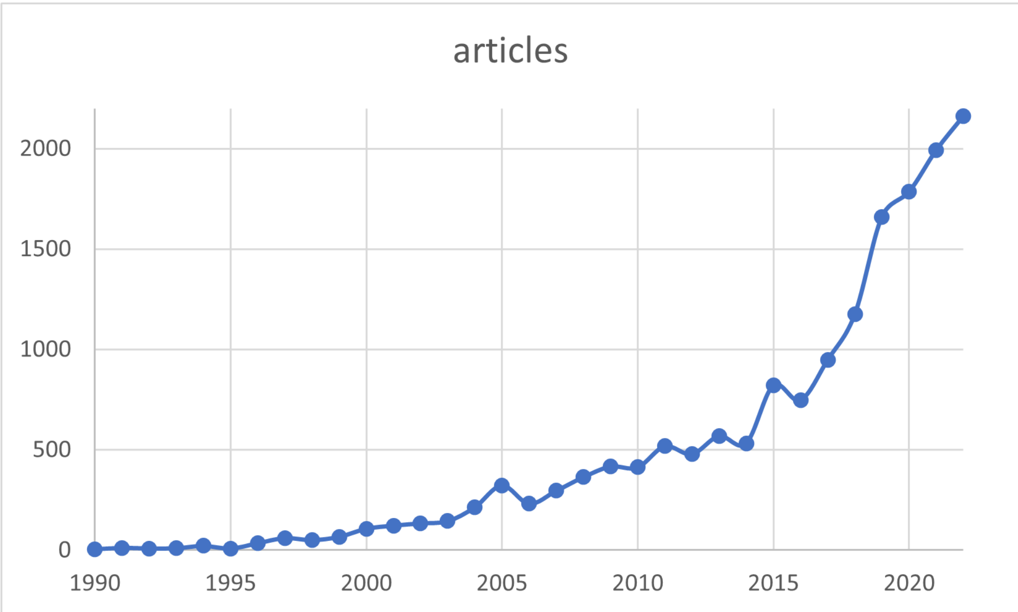


Figure 2.1: Evolution of "Precision Agriculture" articles since 1990

2.2 Background

The technique of spraying pesticides and chemicals is a usual operation in agriculture today. Meanwhile, besides being efficacious, these products can harm the soil and the food quality. This practice has caused many wild plants and animal species to go extinct regionally or nationally and has profoundly changed the functioning of agroecosystems [11].

For almost three decades, to surpass these problems, the precision agriculture technique has been studied and evolved into what we know today. In 1995, the consequences of applying varying herbicide dosages were tested, concluding that there were advantages although unacceptable dynamic errors, and it was a necessary improvement on the control algorithm [12].

Later, in 2009 the concept of precision spraying extended to include pesticide treatments directly sprayed to agricultural plants, with the amount of insecticide treated determined by characteristics such as leaf form and volume [11].

In 2015, a system for providing application rates tailored to canopy volume in pistachio orchards was created. It was developed in this study an electronic control system for detecting and estimating tree canopy dimensions for application rate modification. The results showed that the canopy-sensing, automatically controlled sprayer was successfully developed and operated in a pistachio orchard [13].

After in 2016, has been developed the first study with an automatic selective system, and the result was an autonomous selection system for spraying diseases in specialty crops. These studies concluded that this method could detect from 85% to 100% of the diseased area and that the robot reduced pesticide use from 65% to 85% [14] [15].

Afterward, after years of research, in 2021, the Precise Robotic Sprayer (PRySM), a modular and precision terrestrial sprayer robot capable of functioning independently over rough terrain, was designed. After tests, the researchers concluded that the developed sprayer demonstrated that the approach has significant potential to improve spraying accuracy and precision besides being suitable for use in tiny robots; however, several improvements for future work were identified [2]. Therefore, this technique was believed to allow proportionately increasing degrees of pesticide reduction without compromising biological efficacy.

The 2021 paper proposes the autonomous robotic approach, shown in figure 1.1c. In contrast with other methods that use pneumatic sprayers and hydraulic actuators, this mode uses a fully electrical sprayer. Following the results, several advantages were reported compared to the alternative approach, such as the robustness of working in a challenging environment and being entirely electric. That is beneficial for the soil and enables more effective system control when compared to sprayers based on other methods, allowing for higher velocities along with less complex movements during the spraying procedure, high accuracy, lower losses, and increased efficiency [2].

The main advantages of a fully electrical spray are:

- Simplest style
- Enhanced maneuverability

- Integration of variable-rate technology made easier
- Lighter
- Compatibility with extremely low-volume spraying
- Need neither a PTO nor a hydraulic circuit
- Fewer repairs and leaks

This list of benefits is much more considerable compared to the mechanical approaches. They present a few disadvantages, such as the requirement of batteries, which is likely to be more expensive, and devices with high IP ratings and resistance to extreme temperatures. In contrast, the other methods present more disadvantages than advantages. The developed spray 3D model is represented in figure 2.2.

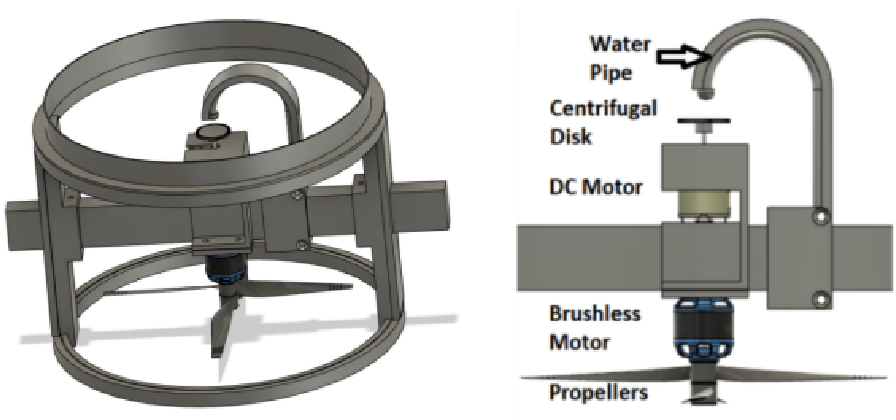


Figure 2.2: Spray hardware 3D model and description [2]

This model was created to be fixed to an aluminum profile. Therefore, to achieve different heights or applications, the user must move the position of the spray drum. To overcome this inconvenience is proposed to modify this prototype into a model with two-degree freedom.

This previous work consisted of extracting descriptors based on the concatenation of several histogram results. The histograms were obtained from mainly six visual concepts such as LPB, GLI, RGBVI, NGRDI, Hue, and Average of vegetation indexes. Using the combination of these six histograms, the researchers extracted some descriptors and applied them in an SVM. The best result obtained was an accuracy of 85%. Combining these factors with the previous advantages, the main goal of this work is to test a large variety of visual descriptors and achieve a better accuracy result.

2.3 Conclusion

Over the past years, the precision agriculture area had enormous growth. Improving past works made possible this technology evolve into what we know today. Collecting data and experiences from other works is necessary to upgrade the work concept.

The study and test of new descriptors combinations and different disposal of the two freedom degree spray is an elementary work pretended to surpass in this dissertation.

Chapter 3

State of the art

In the state-of-the-art analysis, several scientific articles and dissertations were studied to contextualize the problems and their solutions. The chapter is separated into two main sections, one dedicated to the software and another focused on the hardware.

The software section explains the different types of techniques to process leaf images. The hardware section dedicates to studying solutions to the two freedom degrees sprayer.

3.1 Introduction

Today there are many tools that allow us to manipulate different types of data. Over the past years, the machine learning field has exponentially grown. The use of neural networks, SVM, and other techniques of training and testing datasets are commonly used in the precision agriculture area. Moreover, the advance of computer vision made it easier to process image information, and next to it, the emergence of several methods to interpret leaf images facilitates the solution of many projects. R, G, and B will be used as red, green, and blue standards.

3.2 Software

3.2.1 Support vector machines

Support vector machines (SVM) are algorithms used for supervised machine learning models. The benefit offered over other classification methods is the high degree of accuracy they provide.

Resuming, SVM divides the dataset into different classes using a hyperplane and performs classification by creating multidimensional training data from the first training data (Fig. 3.1). Instead of first calculating features from the input, an SVM extracts features directly from the data, exploiting existing patterns [16].

The main idea of the algorithm is:

- Calculate an optimal hyperplane for linearly separable patterns;

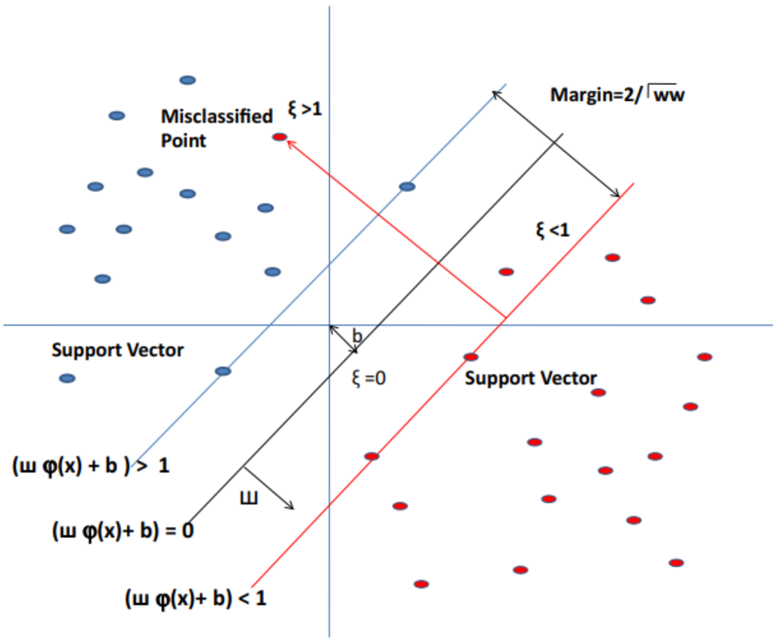


Figure 3.1: SVM example in 2-dimensional space [5]

- SVMs maximize the margin around the separating hyperplane. A subset of training samples fully specifies the decision between two classes: the support vectors;
- Use the Kernel function to extend to patterns that are not linearly separable by transforming the original data to map into a new space.

To minimize the trade-off between the empirical error and complexity, hypothesis space is essential to solving two minimization problems, the SVM classification and SVM regression.

SVM Classification:

$$\min_{\mathbf{f}} \|f\|_K^2 + C \sum_{i=1}^{l} |1 - y_i f(x_i)|_+$$

SVM Regression:

$$\min_{\mathbf{f}} \|f\|_K^2 + C \sum_{i=1}^{l} |y_i - f(x_i)|_\varepsilon$$

The C constant is called the "regularization parameter." This parameter controls the trade-off mentioned earlier [17].

Many coding languages today, such as Python and Java, provide libraries with the above problem solution already implemented; therefore is not relevant to the implementation of an SVM to do a manual solution of the theory. More details about the problem solution can be consulted in this article [17]:

Different SVM implementation techniques have emerged over the past few decades, including Twin SVM, Lagrangian SVM, Least Square SVM, Decision Tree SVM, DAG SVM, and Multi-Kernel Classification. [5]. It is crucial to emphasize that no single categorization method has been proven to be better than others for all datasets. Each article utilizes a different strategy to improve classification accuracy, occasionally combining them. [5].

3.2.1.1 Evaluation Metrics

Multiple evaluation metrics can be used to determine the quality of an SVM algorithm. The main metrics used in this work will be:

- Accuracy: provides the correctly anticipated percentage of the data points. Accuracy suffers the most significant and well-known issues when datasets are unbalanced;
- Recall: It is the percentage of real positive cases that we accurately predicted;
- Precision: It is the proportion of correctly anticipated positive instances;
- F1 score: The harmonic mean of recall and precision. It reaches optimum one only if precision and recall are both at 100%. Furthermore, if one of them equals zero, then also F1 score has its worst value of zero. If false positives and negatives are not equally bad for the use case, F_β is suggested, a generalization of the F1 score.

With the results of the algorithm tested and trained, these metrics can be calculated using the following equations, where TP are the true positives, FP the false positives, TN the true negatives, and FN the false negatives[18][19][20].

- Precision = $\frac{TP}{TP+FP}$;
- Recall = $\frac{TP}{TP+FN}$;
- Accuracy = $\frac{TP+TN}{TP+FP+TN+FN}$;
- F1 = $2 \cdot \frac{precision \cdot recall}{precision+recall}$.

3.2.2 Local Binary Pattern

The Local Binary Pattern operator is a method that compares a central pixel with its neighborhood to obtain a binary result of the comparison of texture, intensity, or color. By thresholding the NxN-neighborhood of each pixel with its center pixel value and using the result as a binary integer, the operator applies a label to every picture pixel. Consequently, a histogram of the labels is created, which may be utilized as a descriptor. [6]. Fig. 3.2 shows an example of a 3x3 neighborhood threshold. In this case, we can see that the darker pixels are labeled as zero, and equal or lighter pixels are labeled as one.

It is common to find circular neighborhoods in the articles and algorithms published. Setting the sampling points equally spaced in a circumference with the pixel labeled as center brings some advantages. That allows the manipulation of the radius of the neighborhood and the number of sampling points.

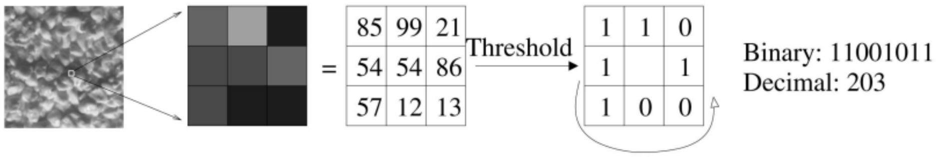


Figure 3.2: LPB exemplification [6]

The LPB has many sorts of disposal. The picture region is flat where the surrounding pixels are all black or white, as seen in Fig. 3.3. "Uniform" patterns are groups of continuous black or white pixels that can be perceived as corners or edges. The pattern is deemed "non-uniform" when pixels alternate between black and white.

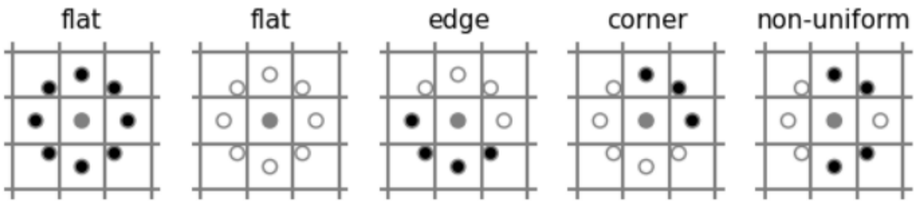


Figure 3.3: LPB types of disposal [7]

3.2.3 Hue Histogram

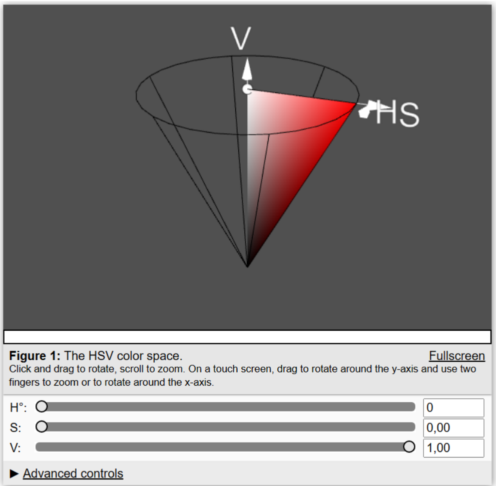
Hue is the H from the HSV color model component and is represented by a number between 0 and 360 degrees. In Fig. 3.4, there is an example of the variation of the hue component. Each degree corresponds to the color location in the color wheel. As the hue value increases from 0° to 360°, the color shifts from red to orange, yellow, green, cyan, blue, magenta, and finally back to red.[21].

In leaf detection, the hue value is adjusted to emphasize the leaf color from the background. So, it is crucial to assign a threshold value that distinguishes ground, sky, or other objects in the crop (blue, brown) from plant leaves (green). To do so is necessary to calculate the histogram of the hue component for the green leaves.

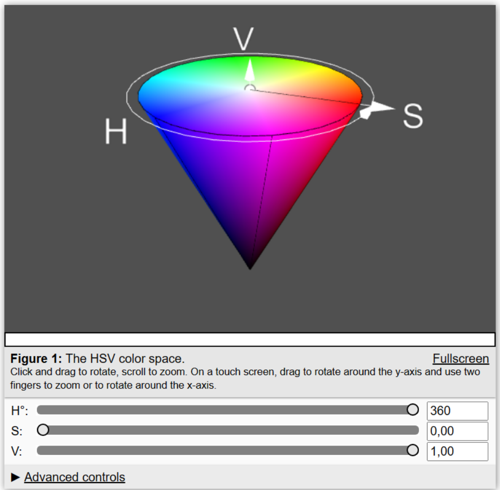
The value of the hue can be calculated by the following formula [22]:

$$hue = arctan(\frac{\sqrt{3}(R-G)}{R+G-2B}) \tag{3.1}$$

Although having this formula, the OpenCV library provides tools to calculate the hue histogram without applying this formula directly, given that the library allows the conversion of an image from BGR or RGB to HSV.



(a) 0 degree hue



(b) 360 degree hue

Figure 3.4: Lukas Stratmann color website[8]

3.2.4 Vegetation Indices

This subsection aims to study and present the different types of vegetation indices. These indices will be used in the histogram concatenation. With this information, it is possible to extract descriptors to insert in the SVM. After train and testing, it is possible to compare the values that give the best accuracy results.

This work will only use and study RGB indices, which hold the RGB bands. This choice is due to the robot's RGB camera coupled to the system.

3.2.4.1 Green Leaf Index

With the pixels analysis of leaves and stems pictures, it was observed that they had higher green digital numbers than red or blue [23]. It happens because of the relation between the reflectance in the green channel compared to the other two visible light channels (red and blue) [9]. Based on the previous works is known that chlorophyll absorbs red and blue but reflects green [23].

The computation of the GLI value is obtained by the following expression[23]:

$$GLI = \frac{2G - R - B}{2R + G + B} \tag{3.2}$$

R, G, and B represent the red, green, and blue channels. The GLI range varies from -1 to 1. The lower the greenness index, the greater the green reflection compared to the other color channels. The value -1 represents a complete reflection in the green channel, and no reflection in the other two color channels [9]. Fig. 3.5 shows three examples to compute the green value. The X-axis depicts a simplified spectrum spanning 400 to 1,000nm. The relative reflectance for each wavelength is shown on the Y-axis. The red, green, and blue channels should be centered about $0.67\mu m$, $0.45\mu m$, and $0.55\mu m$, respectively [23].

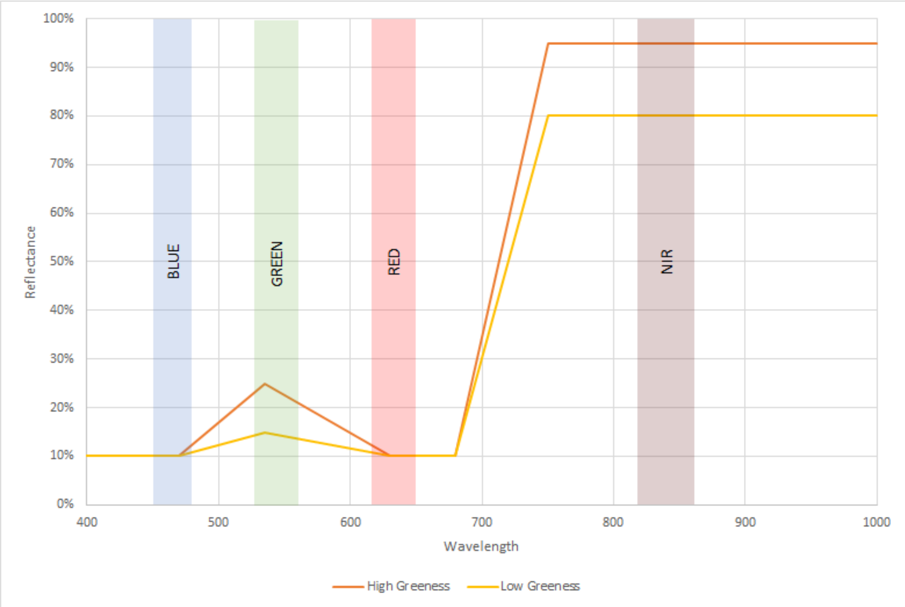


Figure 3.5: Greenness calculation example [9]

3.2.4.2 RGBVI

This vegetation index was first introduced in 2015. The rates of vegetation that employ the visible band (RGB) are significant remote sensing methods for monitoring vegetation. This remote sensing is also a result of the indexes' adaptation to commercial cameras, the latter of which is free of complicated sensors that require high power acquisition and provide wider dissemination and use for more specialized uses [24].

The RGBVI is defined as the normalized difference of the squared green reflectance and the product of blue × red reflectance as shown in the equation below [25].

$$RGBVI = \frac{(G)^2 - (B * R)}{(G)^2 + (B * R)} \tag{3.3}$$

3.2.4.3 NGRDI

The Normalised Green and Red Difference Index (NGRDI) are calculated from the reflectance in the green and red parts of the spectrum, which can be derived from true color images [26]. It was developed to make up for differences in exposure settings that the digital camera selected when taking field aerial images. These variances may result in significant differences in color bands with the same reflectance [27].

$$NGRDI = \frac{G - R}{G + R} \tag{3.4}$$

Except in sparse vegetation, the index is moderately sensitive to changes in soil and atmospheric backdrop. It can become saturated in dense vegetation conditions when the leaf area index becomes high [28]. The G - R component is used to distinguish between green plants and background soil, while the G + R component is used to normalize for differences in light magnitude between photos [27].

3.2.4.4 Redness Index

This index was developed as a solution for surpassing the problem of the detection of vegetation when they are dispersed and present in arid soils [29]. In short, the RI is a correction factor for soil color's effect on vegetation indices [30]. As mentioned in the Huete work, soil color and brightness are the two factors that most interfere in detecting low coverage rates. The following equation defines the calculation of the index.

$$RI = \frac{R-G}{R+G} \tag{3.5}$$

As this work wants to detect the number of leaves in a determinate ROI, this index can help classify low quantities of leaves.

3.2.4.5 Excess Green Index

This index aims to distinct plants from non-plants. It is an interesting method to be used in a crop because ExG created nearly binary pictures that produced a sharp contrast between the plants and the dirt. [27]. The chromatic coordinates of the spectrum give the result of ExG. The following equation gives the index value:

$$ExG = 2g - r - b \tag{3.6}$$

Where the chromatic coordinates r,g, and b can be defined as:

$$r = \frac{R^*}{R^* + G^* + B^*};\ g = \frac{G^*}{R^* + G^* + B^*};\ b = \frac{B^*}{R^* + G^* + B^*} \tag{3.7}$$

The asterisk indicates that R, G, and B values must be normalized between 0 and 1, divided by the maximum value.

$$R^* = \frac{R}{R_{max}};\ G^* = \frac{G}{G_{max}};\ B^* = \frac{B}{B_{max}} \tag{3.8}$$

where R, G, and B are the actual pixel values from the images based on each channel and R_{max} = G_{max} = B_{max} = 255 [27].

From Woebbecke's work [31] was developed the following variants of the index:

3.2.4.5.1 Excess Red Index As the ExG, this index aims to separate leaves from non-leaves.

Testing the segmentation of leaf regions from the background, the ExR approach was introduced and compared with ExG since there are 4% blue and 32% green cones in the human retina compared to 64% red cones [27]. The experiment was successful but inaccurate compared to ExG [32].

3.2.4.5.2 Excess Green minus Excess Red Index Combining ExR and ExG methods was developed to separate the plants with Exg and the background with ExR. This approach can be defined as the difference between the previous methods [27][33]:

$$ExGR = ExG - ExR \tag{3.9}$$

3.2.4.5.3 Modified Excess Green Index For this strategy, experiments were conducted in real-time under uncontrolled illumination. The proposed method effectively converted the color image to grayscale. After converting, the image was binarised with a threshold method. The MExG approach was remarkably resilient to shifting lighting conditions; hence classification between plant and soil regions was effective. The MExG method outperformed the ExG method for segmentation [27] [34]. The method can be defined as follows:

$$MExG = 1.262G - 0.884R - 0.311B \tag{3.10}$$

3.2.4.6 Colour Index of Vegetation Extraction

Research using soybean and sugar beet fields served as the foundation for the CIVE proposal. This approach was suggested to distinguish green plants from the background. The CIVE result can be calculated by:

$$CIVE = 0.441R - 0.811G + 0.385B + 18.78745 \tag{3.11}$$

This method has better plant segmentation than NIR because it places more attention on green spaces [27].

The accuracy of the plant status estimation utilizing the examined function could have been more satisfactory for all plant statuses, although being better than NIR. T. Kataoka aimed to estimate the plant status in a specific area, not every plant [35]. Therefore, it concluded that a method is a positive approach to recognizing certain species of plants in a determined area.

3.2.4.7 Vegetative Index

The VEG approach was developed to achieve acceptable differences between soil and plants. This method consisted of changing the image spectrum from RGB to grayscale. Besides providing good contrast between the soil background and the plants, the approach also is very potent under light variation, which is a great advantage.

The black body law is applied based on physical models of daylight-illuminated shadow correction and is related to the blue, green, and red camera filter bands. In this manner, the researchers discovered that it was possible to categorize and turn RGB photographs into bimodal histograms, resulting in goods that were satisfactorily relevant to the premise used [24].

To perform the segmentation, the following formula was developed:

$$\frac{G}{R^a(B^{1-a})} \tag{3.12}$$

where a is a constant value of $a = 0.667$ [36].

In table 3.1, there is a summary of the primary visual concepts discussed in subsection 3.2.4.

Visual Concept	Vegetation Purpose	Index Type	Plant Segmentation	Main Advantage
LPB	No	GRAY	0	Simple
Hue	No	HSV	0	Easy setting threshold
GLI	Yes	RGB	+	Flexible use
RGBVI	Yes	RGB	+	Simple
NGRDI	Yes	RGB	+	Overcome the differences in exposure settings
RI	Yes	RGB	0	Simple
ExG	Yes	RGB	+	Good contrast between plants and non- plants
ExR	Yes	RGB	0	Simple
ExGR	Yes	RGB	+	Simultaneously apply two segmentations
MExG	Yes	RGB	++	Robust in changing illumination conditions
CIVE	Yes	RGB	0	Great emphasis in green area
VEG	Yes	RGB	+	Robust in changing illumination conditions

Table 3.1: Visual concepts comparison table

3.3 Hardware

Another important part of robot development is the hardware. The concept of DOF is crucial to develop the intelligent sprayer. As this work requires a two-freedom degree robot, it is necessary to contextualize the theoretical base behind it.

The most minor independent variable needed to specify the location of a rigid body in space is known as the DOF. Alternatively said, the variety of motions a body may do. We can define a rigid body as a mechanism when the DOF > 0 [37].

The definition of the term "kinematic connections" is also crucial. Kinematic linkages are components that move motion from one place to another. Joints connect these links. DOF of a kinematic link can be computed using Grubler's rule. This formula states that the number of freedom degrees is determined by subtracting the number of independent constraints from the total of their freedoms.

$$DOF = \sum(freedom\ of\ the\ bodies) - independent\ constraints \tag{3.13}$$

Assuming N is the number of bodies(ground included), J is the number of joints, and m is the constant number that defines the number of degrees of freedom of a body (six for spatial bodies or three for planar bodies), the equation can be rewritten as[38]:

$$DOF = m(N-1) - \sum_{i=1}^{J} c_i \tag{3.14}$$

Moreover, knowing the degree of freedom of movement of one link with another can be deduced by subtracting m from the number of constraints that the joint imposes($f_i = m - c_i$), the final equation obtained is [38]:

$$DOF = m(N-1-J) + \sum_{i=1}^{J} f_i \tag{3.15}$$

The two main movements to consider are rotation and translation.
The translation can be subdivided into three movements:

- Forward - Backward;
- Right - Left;
- Up - Down

Moreover, the rotation can be subdivided into another three movements:

- Pitch;
- Yaw;
- Roll

Fig. 3.6 exemplifies the six-freedom degree movement.

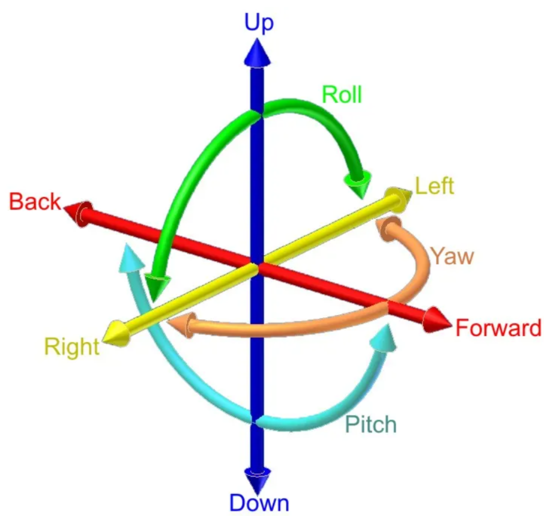


Figure 3.6: Six freedom degree diagram [10]

Considering the theoretical approaches, the next chapter will analyze the best solution to develop a two-freedom degree sprayer. As shown in Fig. 2.2, the last spray hardware built was based on a fixed drum. The roll and yaw movements could significantly improve the base of the drum since that would allow a better coverage area. However, a spray coupled to a two freedom degree robot arm would grant access to more dense and higher foliage.

3.4 Conclusion

This section introduced several methods for extracting vegetation from an image. All approaches have advantages and disadvantages for detecting foliage, and previous studies have shown that combining some strategies often produces positive results. In addition, it was presented the hardware mechanical concepts for the intelligent spray. The DOF's possible movements were discussed to validate the improvement possibilities for the robot spray.

Chapter 4

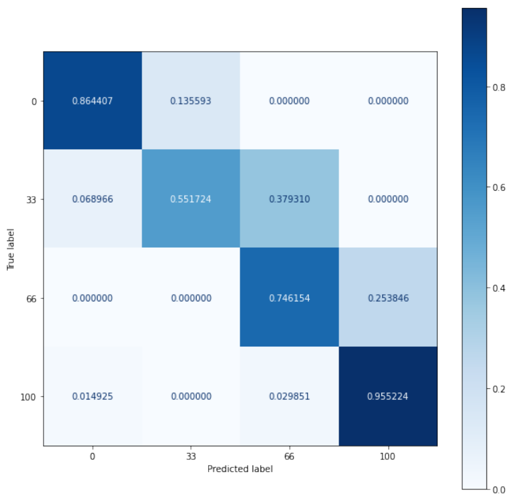
Work plan

4.1 Preliminary work

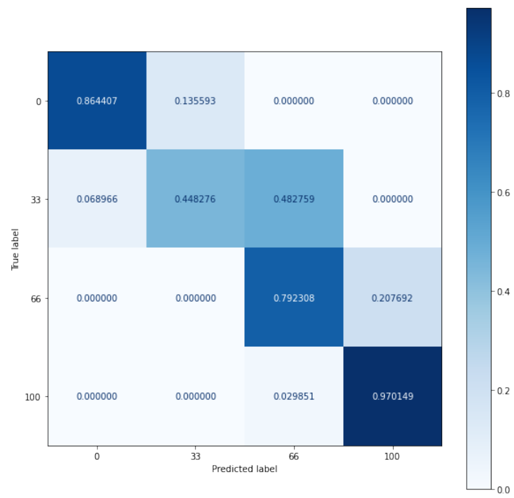
The preliminary work started by studying, testing, and validating the work developed by MSc. André Rodrigues Baltazar in the article "Smarter Robotic Sprayer System for Precision Agriculture"[2].

This preliminary work was proposed as a Computer Vision course unit project. The code was developed in Python using Google Colaboratory. The dataset used is public and can be found in the following link `https://rdm.inesctec.pt/dataset/ise-2021-001`.

The validation consisted of testing two descriptors, one composed only of LBP histograms and another combining LBP, GLI, and HUE histograms. After extracting the descriptors, they were used as input for an SVM. The results obtained are presented in Fig. 4.1



(a) Confusion matrix of descriptor one



(b) Confusion matrix of descriptor two

Figure 4.1: Preliminary work results

The image shows that the descriptor successfully classified the leaf percentage with acceptable accuracy. The accuracy obtained for descriptor one was 80% and 81% for descriptor two; that is, the descriptor had an improvement with the combination of the visual concepts. The results were slightly different from the article results due to the newer version of the libraries and some imprecision.

Table 4.1 presents the detailed results. Moreover, the table 4.2 shows the results for each classification label.

	F1 Score Macro(%)	F1 Score Micro(%)	F1 Score Weighted(%)	Accuracy
Descriptor one	77	80	80	80
Descriptor two	76	81	81	81

Table 4.1: Results of preliminary work

	Accuracy(%)			
Label	0	33	66	100
Descriptor one	90	60	80	78
Descriptor two	91	52	82	81

Table 4.2: Accuracy results for each label

All configurations have an accuracy below 90%, as noted in the article "Smarter Robotic Sprayer System for Precision Agriculture," which is acceptable given the proximity of the classes. As an illustration, we can see that the categorization conflates class 33 with class 0. It is situated at the point where these two classes meet. The 100% class, for instance, is never designated as 0 or 33 percent [2].

In short, the SVM code works and has good scores, although it can be improved. We can see that the algorithm confuses itself with adjacent classes. First of all, the descriptors can be updated to increase the accuracy, that is, include other leaf index features to identify more types of vegetation. Second, updating and expanding the dataset size can be very useful for classification problems. With considerably more data, we can increase the number of classes and achieve more precision in the spray. Expanding the data size can also minimize the classification problem in the 33% class, given that the test samples will also be increased.

4.2 Work plan

The work plan consists of a series of plans and tasks to complete the thesis work. The research plan will follow the following list:

- Acquire a foliage dataset;
- Test different combinations of descriptors with the visual concepts presented in section 3.2 to develop the Perception Algorithm;
- Test and train the descriptors with an SVM;
- Study and design a structure for the precision spray with two degrees of freedom;

- Select the necessary hardware for precision sprayer motion control;
- Control precision sprayer movement in two degrees of freedom;
- Integrating the Perception Algorithm into the Precision Sprayer;
- Solution testing and validation;
- Write the dissertation.

After following the steps above, the work should follow the workflow presented in figure 1.

In Fig. 4.2, is presented the Gantt chart about the preliminary work developed in the "Introduction to Research" course unit and the estimated conclusion dates for each task planned.

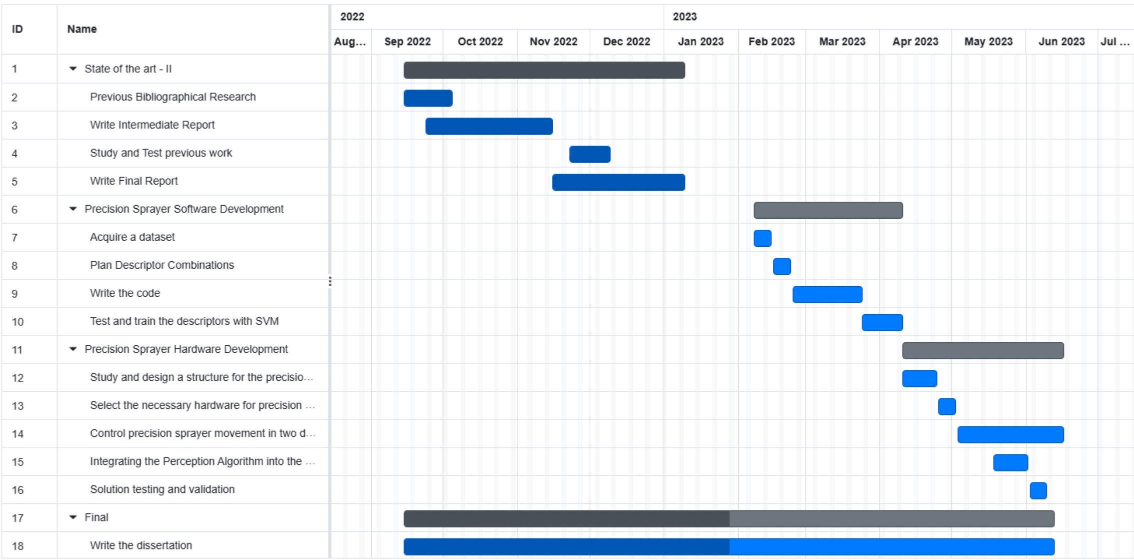


Figure 4.2: Thesis work Gantt chart

Chapter 5

Conclusion

This intermediate report presented the motivations, background, and theory behind the dissertation work. Based on previous and preliminary work, the combination of visual concepts produces significant advantages in some cases. Combining different descriptors can improve the accuracy and raise the F1 score. Another crucial factor in improving the results is expanding the dataset. Acquiring more data to train and test the algorithm achieves more accurate results.

Moreover, adding more than one degree of freedom to the mechanical system give more liberty to the robot. Instead of a fixed jet direction, the mechanism can move and consequently cover more area. The consequence of a larger coverage area is to decrease the number of sprays needed in the robot.

The dissertation work pretends to compile all the conclusions of this intermediate report. These conclusions will help to identify the best solutions in the development of the robot.

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