# Image processing algorithms for a selective vineyard robotic sprayer

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## Abstract
This paper presents image processing algorithms for a selective robotic sprayer in vineyards. Two types of machine vision algorithms were developed to directly spray grape clusters and foliage. The first algorithm is based on the difference in the distribution of edges between the foliage and the grape clusters. The second detection algorithm uses a decision tree algorithm for separating the grape clusters from the background based on a training dataset from 100 images. Both image processing algorithms were tested on data from movies acquired in vineyards during the growing season of 2008. Results indicate high reliability of both foliage detection and grape clusters detection. Preliminary results show 90% percent accuracy of grape clusters detection, leading to 30% reduction in the use of pesticides.

**Keywords**: precision agriculture, Image Processing edge detection, decision tree, machine learning

## Introduction
The use of pesticides is an integral part of modern agriculture. However, wrong use or over use of pesticides is dangerous for the environment, for humans, and for the plant. Chemically-polluted runoff from fields cause contaminated surface and ground waters (Pimental and Lehman, 1993; Tardiff, 1992), and violate ecological balance (Maor, 1993). In addition, it causes medical hazards with approximately 20,000 workers dying from exposure every year (WHO, 1990; Kishi et al., 1995; Pimental et al., 1992; Rosenstock et al., 1991). Due to the environmental and medical hazards and to increasing environmental awareness, there is an immediate need to reduce the use of chemical pesticides in agriculture to a minimum.

Grape cultivation is the most common growth in Israel (Central Bureau of Statistic, 2007) and as such, any reduction in pesticide application will lead to major pesticide savings. Today, vineyards are sprayed homogenously along the vineyard rows, without considering areas with low foliage density or gaps between the different trees. Estimates indicate that 10%-30% of pesticide agent can be reduced by using smart sprayers focused towards foliage only (Ganzelmeier, 2006).

This paper is part of a larger project aiming to design, build, and test an autonomous, site-specific spraying robot for vineyards. The paper focuses on the image processing phase and deals with two types of spraying pesticide techniques: spraying the foliage and spraying the grape clusters. Today, spraying the foliage is done by using a spraying boom which covers the entire height of the foliage (Ministry of Environmental Protection, 2006). The spraying boom is dragged along the row and sprays the entire foliage without considering gaps between trees or the varying density of foliage.

While foliage spraying is done unselectively, spraying the grape clusters is done in one of two ways. Often, a human carries a portable sprayer and sprays the grape clusters individually. This operation is very time and human labor consuming. Alternatively, grape clusters can be sprayed unselectively by adjusting a sprayer boom to the height of the grapes, usually from 50cm to 100cm above ground. Then, the spraying boom is dragged along the row and sprays the entire grape clusters strip. This type of spraying technique wastes a lot of spraying agent and pollutes the environment.

While selective spraying has other incentives also, reducing the use of pesticide is one of them. Here we argue that such savings can be achieved in both the foliage spraying process and in the grape clusters spraying. In particular, we wish to detect gaps between trees in order to reduce pesticides during foliage spraying, and detect grape clusters for selective spraying. A spraying robot equipped with these detection capabilities and a pan\tilt head with a spraying nozzle would be able to spray selectively and precisely, saving significant amount of spraying material.

It should be mentioned that autonomous robotic sprayers have already been proposed and studied. Yuichi (2006) developed a robotic sprayer for vineyards that has the ability to navigate automatically in the vineyard and spray pesticide uniformly on the foliage. Sammons et al. (2005) developed a pesticide spraying robot for greenhouses that moves on greenhouses steam pipes that are used for temperature control. Nishiwaki et al. (2004) developed an automatic weed sprayer for rice fields, which uses an adjustable spraying nozzle and machine vision algorithms to find the rice rows and to adjust the sprayer nozzle to regions between the rice rows. Another selective weed sprayer was developed to classify between weeds and plant using artificial neural networks Zheng et al. (2005).

## Image Processing Algorithms

In this paper we present two types of image processing algorithms: a Foliage Detection Algorithm (FDA) and a Grape clusters Detection Algorithm (GDA).

The FDA is based on the fact that the foliage color is green. After capturing the image, two filters operate on it; one is for removing white pixels (sky, sun, etc.) and the other is to trace the green pixels. These filters are combined to produce the foliage image (Figure 1).

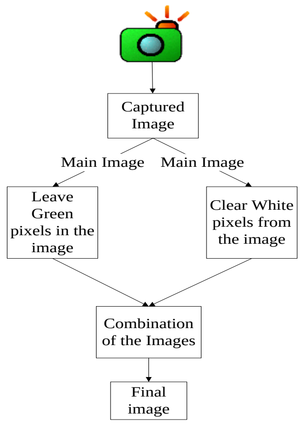


**Figure 1- FDA Block Diagram**

**Figure 2-Captured Image**

**Figure 3-Foliage Image**

Two GDAs were developed. The first GDA is based on the difference of edge distribution between the grape clusters and the foliage. The algorithm was created by examining images from the vineyard and noticing that image regions of grape clusters contain more edges that those found in foliage regions. The GDA is therefore built from three main stages (Figure 4); FDA, edge detection, and thresholding the high edge from the low edge areas.

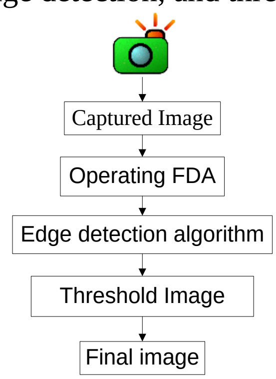


**Figure 4-GDA1 Block Diagram**

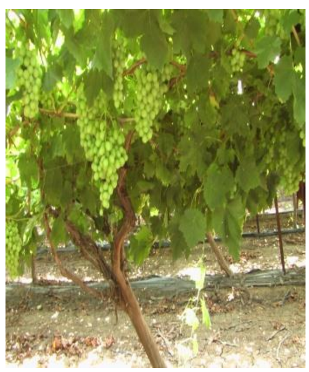

**Figure 5- Captured Image**

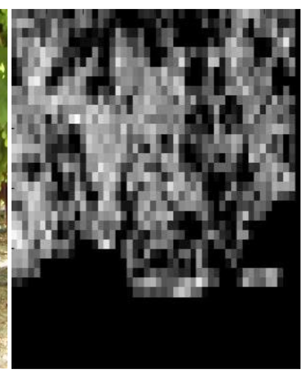

**Figure 6-Edges Image**

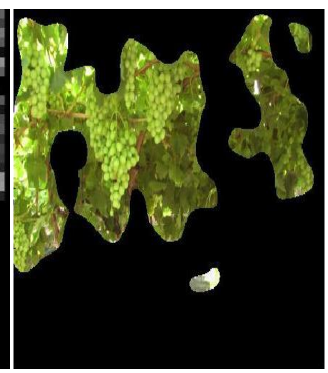

**Figure 7-Final Image**

The second GDA is based on a decision tree algorithm. First, the color image is represented in both the usual RGB representation and the perceptually motivated HSV (Hue, Saturation, and Intensity) representation. Then, supervised patches taken from the grape areas and the foliage areas are used to extract the following parameters from each of the R,G,B,H,S,V channels: mean value, standard deviation, and the mean and standard deviation of the gradient magnitude. Using three patch sizes, we therefore extract 72 different parameters from each image (Table 1) and a total of 1708 samples of these parameters were extracted from the entire image collection. The decision tree was then trained and constructed from these sampled using Matlab® Statistics Toolbox.

| mask diameter = 21 | | | | | | | | mask diameter = 15 | | | | | | | | mask diameter = 11 | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| mean | | | | standard deviation | | | | mean | | | | standard deviation | | | | mean | | | | standard deviation | | | |
| Image | | Gradient Image | | Image | | Gradient Image | | Image | | Gradient Image | | Image | | Gradient Image | | Image | | Gradient Image | | Image | | Gradient Image | |
| R,G,B | H,S,V | R,G,B | H,S,V | R,G,B | H,S,V | R,G,B | H,S,V | R,G,B | H,S,V | R,G,B | H,S,V | R,G,B | H,S,V | R,G,B | H,S,V | R,G,B | H,S,V | R,G,B | H,S,V | R,G,B | H,S,V | R,G,B | H,S,V |

**Table 1-decision tree parameters**

Once the decision tree is constructed, it can be used for classification: the same parameters that were extracted during the learning process are extracted from the given image around each pixel, and then the pixel is classified to grape or non-grape using the decision tree.

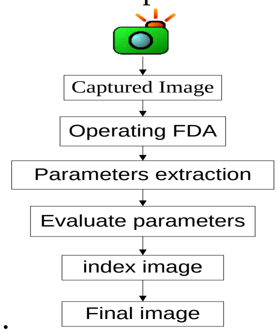


**Figure 8-GDA2 Block Diagram**

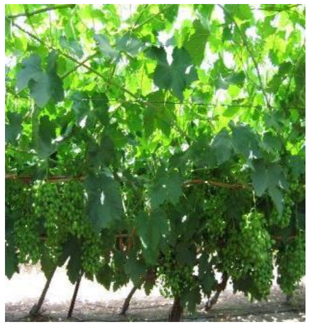

**Figure 9-Captured Image**

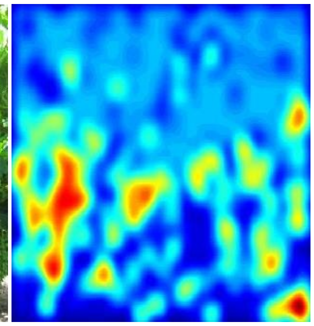

**Figure 10-Index Image**

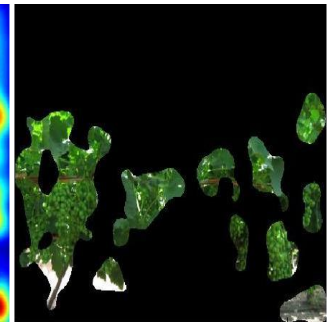

**Figure 11-Final Image**

## Methods

The camera (IDS Inc. uEye USB video camera with a Wide VGA [752 x 480] resolution) was attached to a custom built towing cart specially designed for the image sampling (Figure 12). The cart imitates the movement of a wheeled vehicle so as to ensure the images taken using the cart are as similar as possible to images from moving wheeled robot. The camera was connected to a DELL® Core2 computer. Images were sampled using Matlab® Image Acquisition Toolbox and saved for offline processing. Field experiments were conducted along the growing season of 2008 (mid April till end of July). With an interval of two weeks between experiments, the cart was dragged through the vineyard row and images were taken and stored on the computer. The dragging speed of the cart was between 4~5[Km/h], speed that imitates the speed of a human farmer who sprays.

**Figure 12 - Experimental towing cart**

To obtain a high variety of grape and foliage images, the experiments were performed in two different vineyards, one with green grapes and the other with red grapes. A total of 16 movies were sampled. 100 random images were extracted from these movies and the grape clusters area was marked manually in each image. This set of images was used to evaluate the machine vision algorithms.

*Algorithm evaluation*

The machine vision algorithms were evaluated by comparing the results of the Grape Detection Algorithms (GDA) to manually marked grape clusters area. Two parameters were evaluated: the detection percentage of the marked area and the percent of material that will be saved as a result of using these machine vision algorithms as compared to spraying the whole area.

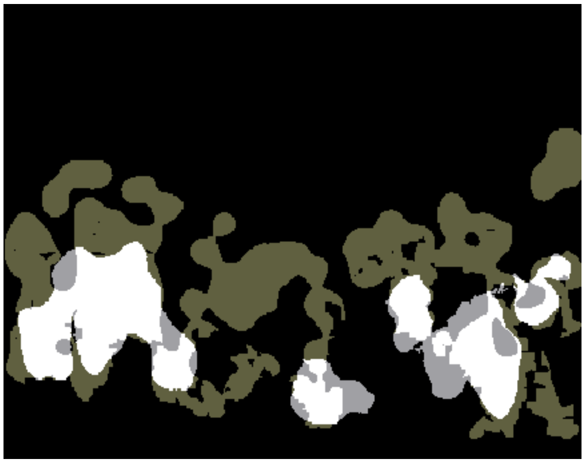

**Figure 13-comparison between marked and machine vision detection**

Figure 13 demonstrates the first parameters evaluation. The figure is divided into four different colors, white, bright gray, dark gray and black corresponding to the true grape areas that the algorithm found (True-True TT), the true grape areas that the algorithm did not find (False-True FT), the areas that the algorithm marked as grape but was foliage (True-False TF) and the foliage area that the algorithm marked as foliage (False- False FF). The percent of TT was the main parameter for the algorithm evaluation because of its important influence on the quality of the grape spraying. The percentage reduction of spraying material was evaluated by comparing to the current spraying method in which the farmer sprays a strip of 50[cm] which contains most of the grape clusters (represented in Figure 14 as the dark gray and white areas). Comparison between this strip and the white area in Figure 14 yields the percentage of saved pesticides.

**Figure 14- Comparison between targeted spraying and traditional spraying**

The detection evaluation parameters (TT TF FT FF) were optimized. Optimization was conducted by changing the influencing variables in the algorithm and setting the range of each of these variables. Every possible combination of the different variables in the range was tested on a set of 100 representative images. For each combination, the mean of the detection quality and the mean of the reduction of pesticides were calculated. The optimization of one variable (threshold value) is shown in Figure 15, where each point represents a different threshold value and the resulting detection quality and pesticide reduction. For example, if the farmer requires 80% grape detection, using the different curves (Figure 15), it is possible to find which parameters to use and what will be the pesticide reduction rate for this detection rate.

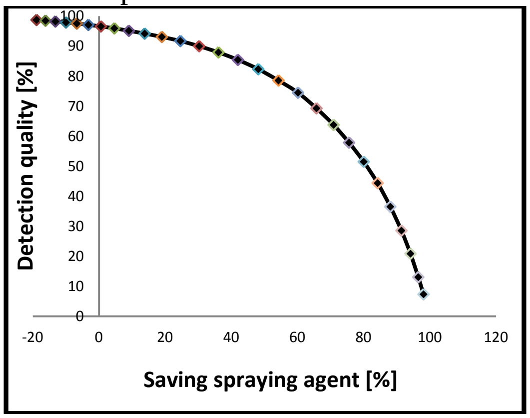


Figure 15- Grape Detection (edge Based)

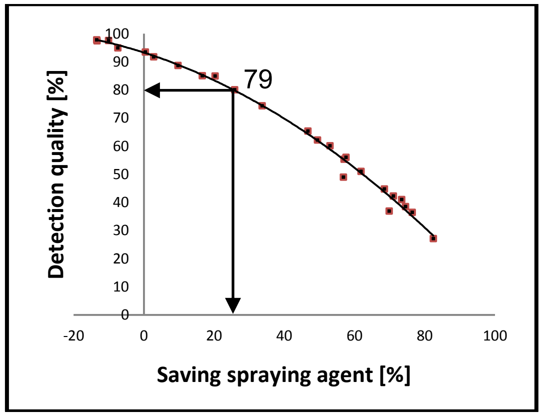


Figure 16– Grape Detection (Decision tree)

## Results

Both Grape Detection Algorithms (GDA), showed high ability to detect grape clusters in the vineyard environment. The edge based GDA show ability to detect up to 90% of the grape clusters with a standard deviation of 12. The Decision Tree based GDA show ability to detect up to 85% of the grape clusters with a standard deviation of 15. Up to 30% of pesticides can be reduced when using the edge base GDA and 25% of pesticides can be reduced when using decision tree GDA. The processing time of the edge based GDA algorithms is 0.65s and the processing time of the decision tree based GDA is 1.43s.

## Conclusions

Machine vision algorithms resulted in high detections of grape clusters which can lead to significant reduction of pesticides in vineyards. Thirty percent of the pesticide material can be reduced while detecting and spraying 90% of the grape clusters. Reduction of 25% of pesticide can be achieved when using GDA based on a decision tree algorithm. It is possible that creating a decision tree from larger datasets will produce better detection results. The machine vision algorithms were tested on images from commercial vineyards while sampling a variety of grape species. Due to that, the future robotic sprayer will not be limited to certain species. In order to implement these algorithms on an operational robotic sprayer, the algorithm processing time should not exceed 1 second for each image (assuming an average driving speed of 5[Km/h]). The first GDA processing time is 0.65s and therefore can be used in real-time machine vision. The second GDA processing time exceeds 1s and therefore is not applicable in its current configuration.

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