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SPECIAL ISSUE

Grape clusters and foliage detection algorithms for autonomous selective vineyard sprayer

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Abstract While much of modern agriculture is based on mass mechanized production, advances in sensing and manipulation technologies may facilitate precision autonomous operations that could improve crop yield and quality while saving energy, reducing manpower, and being environmentally friendly. In this paper, we focus on autonomous spraying in vineyards and present four machine vision algorithms that facilitate selective spraying. In the first set of algorithms we show how statistical measures, learning, and shape matching can be used to detect and localize the grape clusters to guide selected application of hormones to the fruit, but not the foliage. We also present another algorithm for the detection and localization of foliage in order to facilitate precision application of pesticide. All image-processing algorithms were tested on data from movies acquired in vineyards during the growing season of 2008 and their evaluation includes analyses of the potential pesticide and hormone reduction. Results show 90% accuracy of grape cluster detection leading to 30% reduction in the use of pesticides. The database of images is placed on the Internet and available to the public to continue developing the detection algorithms.

Keywords Precision agriculture · Image processing · Edge detection · Decision tree · Machine learning

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1 Introduction

1.1 Overview

Site-specific targeted spraying can lead to reduced pesticide application, thereby, improving sustainability and overcoming environmental concerns [1,2], reducing material costs and human labor, and diminishing medical hazards [3,4]. Currently, spraying in vineyards is conducted homogeneously along the rows, without considering areas with low foliage density or gaps between the grapevines. Estimates indicate that 10–30% of the pesticide agents can be reduced by using smart sprayers targeted towards foliage only [5]. By targeting spraying material only to the grape clusters further reduction can be achieved.

Typically, foliage spraying is done using a spraying boom that covers its entire height. The spraying boom is dragged along the row and sprays the entire foliage without considering gaps between the grapevines or the varying density of foliage. While foliage spraying is done non-selectively; 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 consuming and labor intensive. Alternatively, grape clusters can be sprayed non-selectively by adjusting a sprayer boom to the height of the grapes, usually from 50 to 100 cm above ground. Then, the spraying boom is dragged along the row and sprays the entire grape clusters strip. This type of spraying technique harms the leaves that are being sprayed. Additionally, it wastes a lot of spraying agent, and pollutes the environment.

This work is part of a larger project aiming to design, build, and test an autonomous, site-specific spraying robot for vineyards (Fig. 1). This paper focuses on machine vision aspects that lie at the heart of this site-specific sprayer. The objectives

Fig. 1 Vineyard spraying robot

of the research reported in this paper are to develop a foliage detection algorithm based on machine vision, develop grape cluster detection algorithms based on machine vision and to evaluate the pesticide reduction achieved while using these algorithms to perform site-specific spraying in vineyards. Novel machine vision algorithms were developed to detect gaps between grapevines in order to reduce pesticide use during foliage spraying, and to detect the exact location of grape clusters to target spraying towards them. The algorithms were developed using a new concept that considered pesticide reduction as the main parameter considered in the design while maintain a minimum value of grape clusters detection rate. A spraying robot equipped with these detection capabilities and a pan/tilt head with a spray nozzle would be able to spray selectively and precisely, reducing significant amounts of spraying material and human labor.

1.2 Literature review

Several autonomous robotic sprayers have been developed in the past. An autonomous tractor for spraying was developed at the Robotics Institute of Carnegie Mellon University [6]. Gillis et al. [7] developed a fluid handling system to allow on-demand chemical injection for a machine-vision controlled sprayer. The system was able to provide a wide range of flow rate of chemical solution. Balsari et al. [8] conducted a 3-year experimental study in apple orchards in southern Piedmont to determine the quality of spray deposition on the canopy, the incidence of ground losses, and drift effect according to the sprayer adjustment. Results indicated that the application of reduced volumes (300–500 l/ha) calibrated according to the plants' growth stage enables better coverage of the target and reduces ground losses, although increasing drift risks were registered when fine droplets were sprayed.

Manor et al. [9] used turbulent air-jet nozzles, which helped to penetrate into even dense canopies and accurately deposit the droplets on the different leaves on both sides. By using several turbulent air-jet nozzles, vineyard sprayer accuracy was adjusted.

Wiedemann et al. [10] developed a spray boom that would sense mesquite plants. Sprayers were designed for tractors and all-terrain vehicles. Controllers were designed to send fixed duration pulses of voltage to solenoid valves for spray release through flat-fan nozzles when mesquite canopies interrupted the light. The levels of mesquite mortality achieved were equivalent to those levels that have been achieved by ground crews hand spraying the same chemical solution.

A machine vision sensing system and selective herbicide control system was developed and installed on a sprayer by Steward et al. [11]. The system operated with an overall accuracy of 91%. Significant differences in pattern length variance and mean pattern width were achieved across speed levels ranging from 3.2 to 14 km/h. Spray patterns tended to shift relative to the faster travel speeds. A precision sprayer was developed and tested with a robust crop position detection system [12] for varying field light conditions for rice crop fields. Zheng [13] developed a tree image processing, tree crown recognition, and smart spray execution system. The tree imaging system included a CCD camera, an image grabber, a computer, and experimental setup. The tree crown recognition system based on BP neural networks developed as a method for spraying of pesticides depended greatly on the tree crown type. Six typical tree crowns (cone, spherical, cylindrical, umbellate, etc.) could be determined. The spray execution system consisted of a spraying table, nozzles, solenoid valves, and relays. Similarly, autonomous operation of a speed-sprayer in an orchard was achieved using fuzzy logic control of image processing and ultrasonic sensors, and steered by two hydraulic cylinders [14]. Ogawa et al. [15] developed a spraying robot for vine production and demonstrated that the robot is able to spray more uniformly than a human operator and to reduce the amount of spraying agent; no quantitative results were reported (Table 1).

2 Machine vision algorithms

In this work, machine vision algorithms were developed for the two critical aspects of selected vineyard spraying: A *Foliage Detection Algorithm* (FDA) to detect foliage and *Grape clusters Detection Algorithms* (GDA), to detect

Table 1 Recent work on robotic sprayers

Application	Sensor	Results	Reference
Rice	NIR	Reduced pesticide use (no quantitative results)	[12]
Clean road shoulder	Color CCD	Reduced pesticide use by up to 97%	[16]
Weed sprayer	Color video	Reduced up to 91% with max speed of 14 km/h	[11]
Orchards	Color + Ultrasonic	Not reported	[14]
Weed in cotton	Color CCD	Sprayed 88.8% of weed while correctly rejecting and not spraying 78.7% of cotton	[17]
Grapes	Ultrasonic	Not Reported	[15]
Tomatoes	RGB camera	8% Incorrect spray (4 of 51)	[18]
Palms	Stereo camera	Scale-down model proved the ability to track palm trees	[19]
Greenhouses	CCD camera	Presented the ability to navigate in artificial greenhouse	[20]
Weed control	USB camera	83% Success rate with less than 3 s for target	[21]

individual grape clusters. The bulk of this section describes these algorithms.

The *Foliage Detection Algorithm* is based on the fact that the foliage color is green. Two filters operate on the captured image; one removes white pixels (sky, sun, etc.) and the other traces the green pixels. These filters are combined to produce the foliage image (Fig. 2). The FDA is not designed to separate the grapevine foliage close to the camera from the foliage of a grapevine in the next row. Such a separation is not necessary in order to identify the grapevine foliage and the grapes clusters.

FDA—Foliage detection algorithm pseudocode

Input: Captured Image

Output: Binary image that represents the foliage region only

```
For all pixels in main image
  If {Red channel > 190 & Green channel > 190 & Blue channel > 190}
    Pixel RGB value= 0
  End if
  If {Green channel > Red channel & Green channel >
      Blue channel & Green channel > 70}
    Leave pixel in image
  Else
    Pixel RGB value =0
  End if
End for
```

Three *Grape Detection Algorithms* were developed. The first GDA (GDA1) is based on the difference in edge distribution between the grape clusters and the foliage. The algorithm was created by examining images from the vineyard and noticing that regions of grape clusters contain more edges than those in foliage regions. GDA1 includes three main stages (Fig. 5): FDA, edge detection, and thresholding the high-density edge from the low-density edge areas. The edge detection algorithm was based on the Canny edge detection algorithm [22]. The Canny algorithm was empirically selected after experimenting with different edge detection algorithms on an assortment of 100 grape images. Examples of different edge detection methods are shown in Fig. 3. These edge detection methods operated after converting the image to a gray-scale image. Quantitative analyses of the number of edges in the image are presented in Fig. 4 for average results of 100 vineyard edge images. Results indicated that the Canny algorithm produced the most highly detailed edge images (Figs. 3, 4); hence, it was selected for this assignment. These results correspond to previous research [23, 24].

GDA1 - Edged mask based algorithm pseudocode

Input: Captured Image

Output: Index Image that contains only grape clusters

```
Operating FDA
For all image channels
  Operate Canny algorithm
End for
Gray_Image=sum of canny algorithm
Index Image = Smooth Gray_Image using two-dimensional convolution
For all pixels in Index Image
  If {pixel value<threshold}
    Pixel=0
  End if
End for
Delete small area objects from Index Image
Return Index Image
```

GDA2 is based on a decision tree algorithm. First, the color image is represented both in the common RGB representation and in 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, and V channels: mean value, standard deviation, and the mean and standard deviation of the gradient magnitude. Using three patch sizes, 72 different parameters were extracted from each image (Table 2) and a total of 1,708 samples of these parameters were

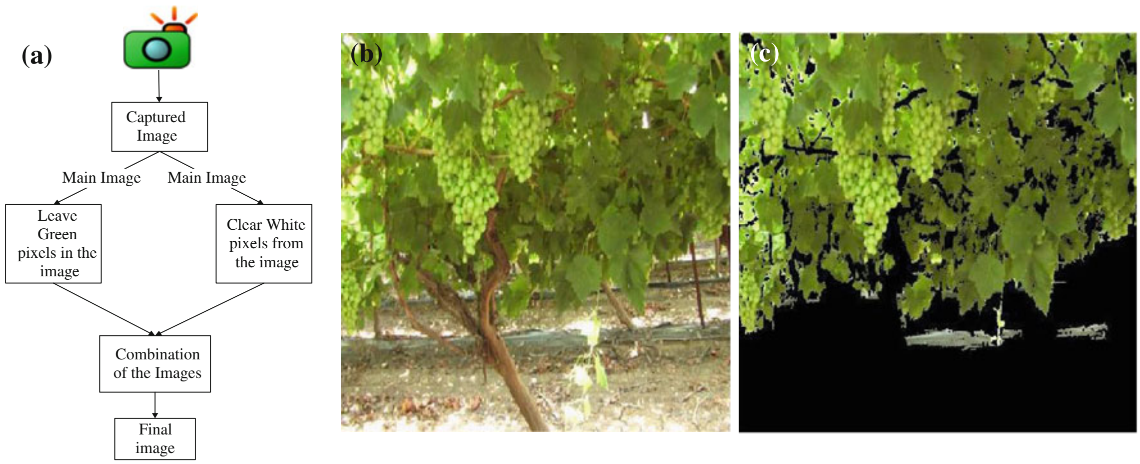

Fig. 2 FDA. (**a**) Block diagram of the algorithm; (**b**) captured image; (**c**) final foliage image

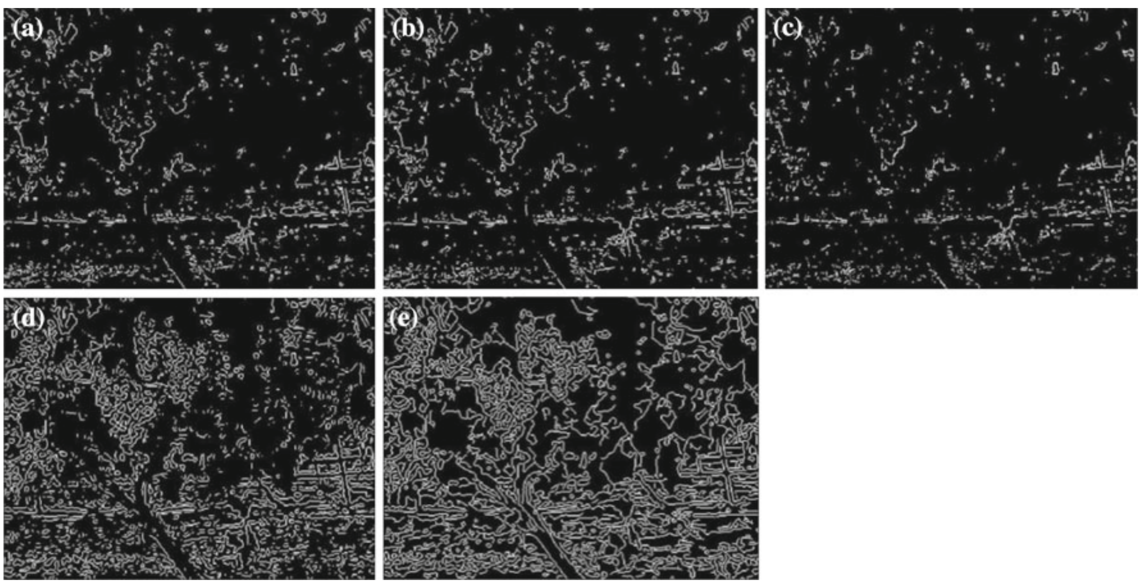

Fig. 3 Different edge detection methods. (**a**) Sobel; (**b**) Prewitt; (**c**) Roberts; (**d**) Laplacian or Gaussian; (**e**) Canny

extracted from the entire image collection. Pearson's correlation [25] was used to filter the parameters that have weak correlation to the classified data: high Pearson correlation represents high correlation between the parameter and the classification. All parameters with a Pearson correlation <0.5 were removed from further consideration. The most significant parameters that were selected using the correlation test were the mean gradient magnitude of the R, G, B, and V channels, all exhibiting Pearson correlation above 0.6. Interestingly enough, this result supports the approach taken in GDA1 which is based on edges density in the image.

Training the decision tree was done using the C5.0 algorithm [25]. The dataset was divided into two groups of 70 and 30% for training and testing, respectively, as commonly practiced. Once the decision tree was constructed, it was used

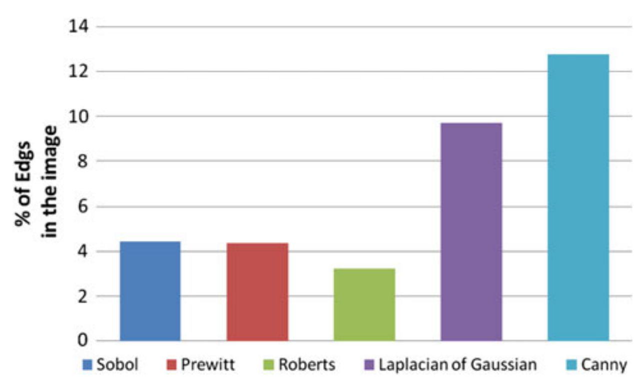

Fig. 4 Quantitative analyses of edges in images

for the classification: the same parameters that were extracted during the learning process were extracted from the given image around each pixel, and then each pixel was classified as grape or non-grape using the trained decision tree. Selected results of GDA2 are shown in Fig. 6.

GDA2 - Decision tree algorithm pseudocode

Input: Captured Image

Output: Index Image that contains only grape clusters

```
Operating FDA
For all pixels in Capture image
  Locate the center of the mask at the pixel
  Extract features from the mask
  Operate decision tree classification on the features
  {
   Return Gray_Image = 0 in case of foliage, 1 in case of grapes
  }
End for
Index Image = Smooth Gray_Image using two-dimensional convolution
For all pixels in Index Image
   If {pixel value<threshold}
     Pixel=0
   End if
End for
Delete small area objects from Index Image
Return Index Image
```

GDA3 is based on pixel comparison between edge representations of the captured image with a predesigned edge mask that represents grapes. A large number of overlapping pixels between the edged image and the edge mask indicates that the area in the image is similar to the area in the mask and therefore a high probability for a grape cluster. The algorithm uses a moving average and compares the mask over the edged image using two-dimensional convolutions. Four-edge masks were evaluated (Fig. 7): (a) edge mask of single grape, (b) edge mask of grape cluster, (c) perfect circle with varied thickness and diameter of one grape with zero value at the center, and (d) perfect circle with varied thickness and diameter of one grape, with negative value at the center. Unlike the third mask, the fourth mask was designed to distinguish between circular edged patterns with and without response in its interior (which would be less preferable in terms of hits).

Given the proposed alternatives, the best mask for the algorithm was selected using the methodology described in Sect. 4. Figure 8 presents descriptive results of GDA3.

GDA3 - Edged mask based algorithm pseudocode

Input: Captured Image

Output: Index Image that contain only grape clusters

```
Operating FDA
For all image channels
Operate Canny algorithm
End for
Gray_Image=sum of canny algorithm
For all pixels in Gray_Image
  Locate the center of the mask at the pixel
  Gray_Image (pixel)= Sum the number of coincident pixels
End for
  Index Image = Smooth Gray_Image using two-dimensional convolution
  For all pixels in Index Image
    If {pixel value<threshold}
      Pixel=0
    End if
  End for
  Delete small area objects from Index Image
  Return Index Image
```

3 Experimental methods

The camera (IDS Inc., uEye USB video camera with a Wide VGA [752 × 480] resolution) was attached to a custom-built towing cart designed specifically for the image sampling test (Fig. 9). This 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 taken from a moving wheeled robot (including the minor image blur occurred for exposure during motion). The camera was connected to a DELL® Core2 laptop computer. Images were acquired using Matlab® Image Acquisition Toolbox and saved for offline processing. The images were captured under natural illumination field conditions with manually controlled exposure which was set to a constant value. Field experiments were conducted during the growing season of 2008. The cart was dragged through the vineyard row and images were captured at a rate of 30 fps and stored on the computer. We repeated this process every 2 weeks from mid April to the end of July 2008. The dragging speed of the cart was set at 4–5 km/h, to imitate the normal speed of manual spraying.

To obtain a large 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 100 random images were extracted from 16 different movies that were sampled in the field. For comparison and algorithm test accuracy, the grape cluster areas were marked manually in each image. The whole dataset of raw images is available for public use and evaluation on: http://www.hl2.bgu.ac.il/users/www/8141/Vineyard%20Images/. The three GDAs are not color based and therefore not sensitive to the grapes' color (i.e., green vs. red).

4 Imaging evaluation methodology

The machine vision algorithms were evaluated by measuring the reduction in applied pesticide materials compared to the amount of material used when spraying the whole area non-selectively.

Usually, performance of detection algorithms are measured through detection rates which include the number of correct detections and the number of false alarms [26–29]. Our novel approach is to measure performance using maximal pesticide reduction while maintaining high target detection rate. High target (foliage\grape clusters) detection rate usually increases as also false alarms, which is reflected by low pesticide reduction. We aim to find the optimal point which leads to maximum pesticide reduction for a certain level of target detection rate (i.e., minimum false alarms for a certain detection rate).

The detection rate was calculated by comparing the GDA's results to ground truth data marked manually by expert human observers. The evaluation of the detection rate is

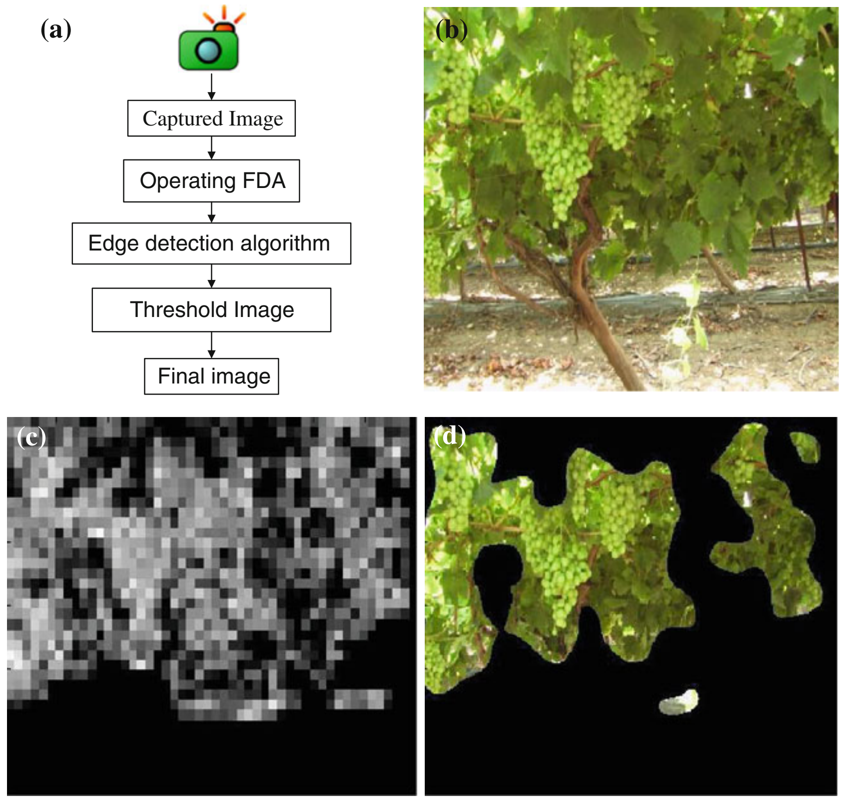

Fig. 5 GDA1. (**a**) Block diagram of algorithm; (**b**) captured image; (**c**) edges image; (**d**) final grape image

Table 2 Decision tree parameters

Mask diameter = 11							
Mean				Standard deviation			
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
Mask diameter = 15							
Mean				Standard deviation			
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
Mask diameter = 21							
Mean				Standard deviation			
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

demonstrated in Fig. 10. The figure is divided into four different color-coded regions as defined in Table 3—white (TP), bright gray (FP), dark gray (TN), and black (FN). The detection rate was calculated as true grape detection (white area, TP) divided by the total area of grapes in the image (white, TP, and dark gray, TN areas which is equal to TP+TN).

The percent reduction of spraying material was evaluated by comparing the current spraying method in which the farmer sprays a strip of 50 cm that contains most of the grape clusters (represented in Fig. 10 as the dark gray and white areas). Comparison between this strip and the white area in Fig. 11 yields the percentage of reduced pesticides.

The aim is to maximize the pesticide reduction while maintaining 90% successful detection rate which was defined as the target detection rate for the analyses conducted. By changing algorithm parameters, the successful detection rate can be later adjusted by the end user according to the grow agronomy necessity.

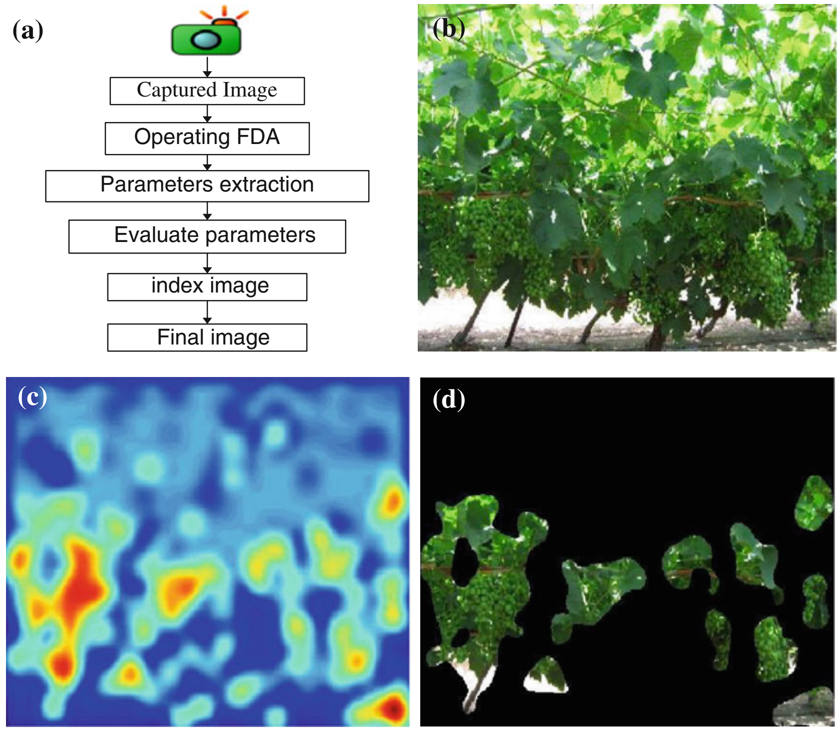

Fig. 6 GDA2. (**a**) Block diagram of algorithm; (**b**) captured image; (**c**) index image; (**d**) final image

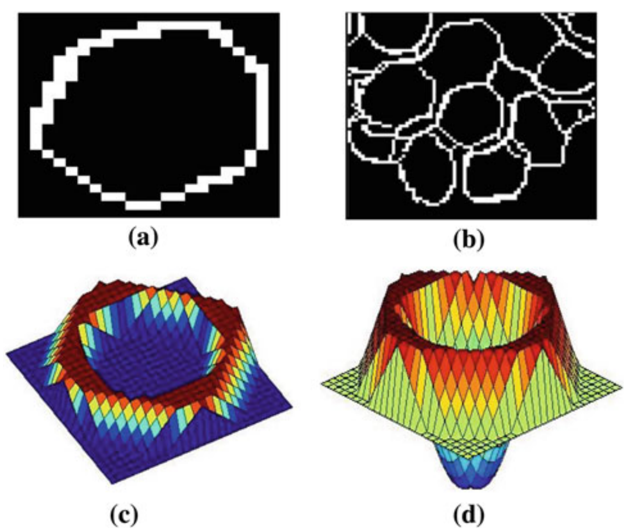

Fig. 7 Four edge masks. (**a**) Single grape; (**b**) grape cluster; (**c**) center zero; (**d**) negative center

The detection evaluation parameters (TP, TN, FP, and FN) were selected to find the combination resulting in optimal pesticide reduction. Pesticide reduction was optimized by changing and resetting the value of variables assimilated in the GDAs (e.g., threshold values, size of small objects to be removed, parameters for the gray image smoothing using two-dimensional convolution). An example of this optimization is shown in Figs. 12, 13 for optimizing the threshold value of GDA1 and GDA2, respectively. Using these graphs, the end user can prefer the desired detection rate (dash line) by selecting the proper threshold value and realize the potential of pesticide reduction (full line), respectively.

Every possible combination of the different variables in the range was tested on the dataset of 100 representative images. For each combination, the mean of the detection rate and the mean of the pesticides reduced were calculated. An example of the optimization of one variable, the threshold value, is shown in Fig. 14, where each point represents a different threshold value and the resulting detection rate and pesticide reduction. For example, if the farmer requires 80% detection rate, using the different curves (Fig. 14) , it is possible to find which parameters to use and the pesticide reduction for this detection rate. From these figures we can see that GDA1 results in improved pesticide reduction as compared to GDA2 (50 vs. 25%).

5 Results

5.1 Robot speed in relation to the machine vision processing time

The robot's spraying speed relative to the algorithm processing time is important for real-time implementation. The following condition must be met: $v \cdot t \leq x$, where v is the robot's speed, t is the machine vision processing time, and x is the real-world field-of-view length. Laboratory measurements showed that the field of view length as perceived by the camera is 2 m, with 1.5 m distance from the camera to the grape clusters. The robot speed as related to the processing

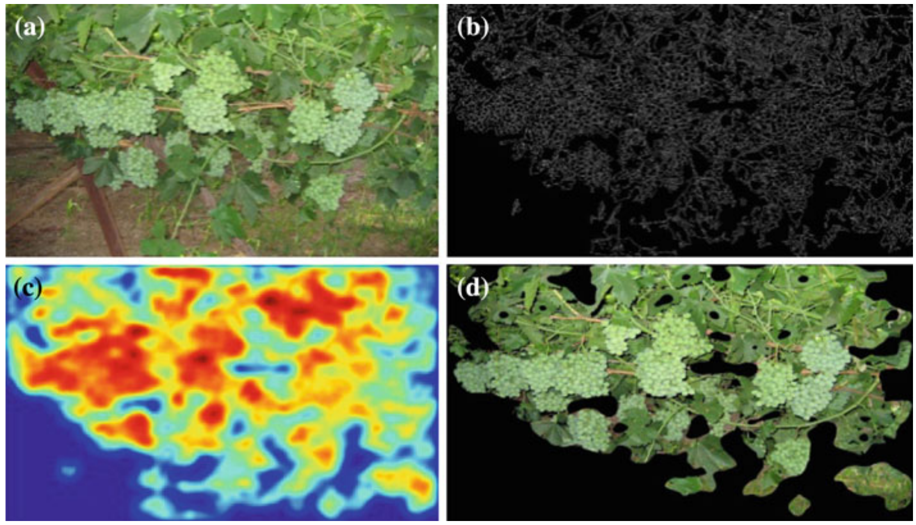

Fig. 8 GDA3. (**a**) captured image; (**b**) edged image; (**c**) index image; (**d**) final image

Fig. 9 Experimental towing cart

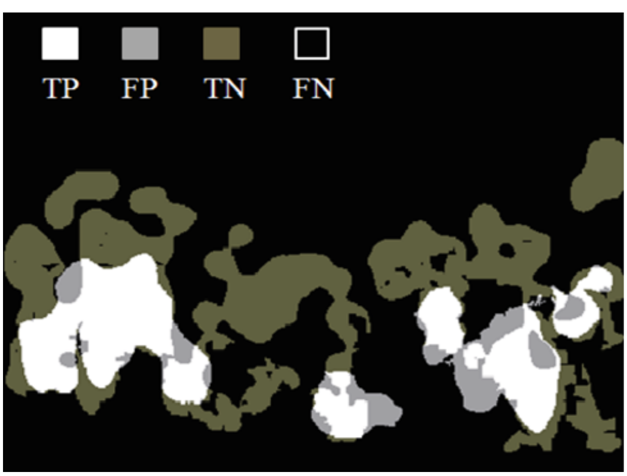

Fig. 10 Comparison between marked and machine vision detection

time can be calculated by using $v \leq x/t$ and substituting $x = 2\,\text{m}$. The maximal robot speed as a function of the processing time is shown in Table 4.

5.2 Saving potential

Saving potential is the percent of maximal feasible saving possible in a given image. The *saving potential* depends on the percent of grape clusters in the given image. *Saving potential* of 100 means that there are no grapes in the image and there is no need to spray. The *saving potential* is inversely proportional to the percent of grape clusters in the image. The relation between the percent of grape clusters in real field images to the *saving potential* is shown in Fig. 15. The *saving potential* is increased with a smaller number of grape clusters in the image. Such conditions of few grape clusters could be a result of images taken early in the season or a gap between the grapevines.

5.3 Imaging results

Three of the four masks suggested for GDA3 resulted in similar pesticide reduction (Table 5), indicating the validity of using an artificial perfect circle mask as an alternative to masks created from real-world edged image. Furthermore, in future research the size (diameter) of the artificial circle mask can be updated dynamically during the field process. These masks are sensitive to varying grape size and in order to use this algorithm throughout the growing season the masks size must be adjusted. A self calibration process can be developed to adjust the mask size to the changing grapes size.

The performance of the three GDAs is summarized in Table 6 indicating reduction between 25 and 30% of pesticide. The detection of grapes as grapes (TP) is more than 90%, which is considered very high with respect to other agriculture detection systems. The overall detection results show high ability to detect grape clusters in the vineyard environment.

Table 3 Color codes for detection classes

Name	Color	Description
TP (True Positive) **White**		Represent the true grape areas that the algorithm marked as grapes (defined also as *Hits*).
FP (False Positive) **Bright gray**		Represent the true grape areas that the algorithm did not find. (defined also as *Miss*)
TN (True Negative) **Dark gray**		Represent the areas that the algorithm marked as grape but was foliage (defined also as *False Alarms*).
FN (False Negative) **Black**		Represent the foliage area that the algorithm marked as foliage. (defined also as *Correct Rejection*)

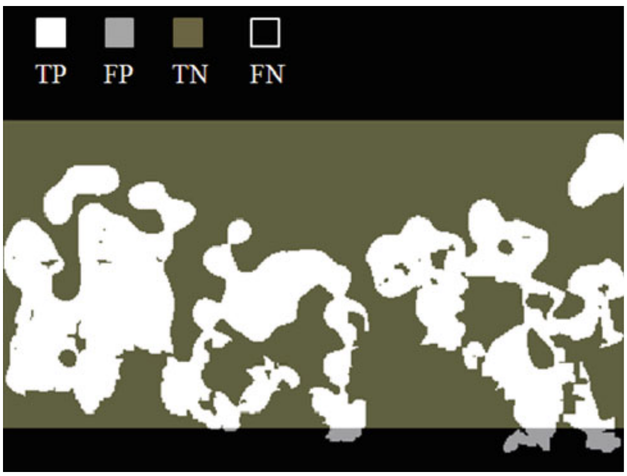

Fig. 11 Comparison between targeted spraying and traditional spraying

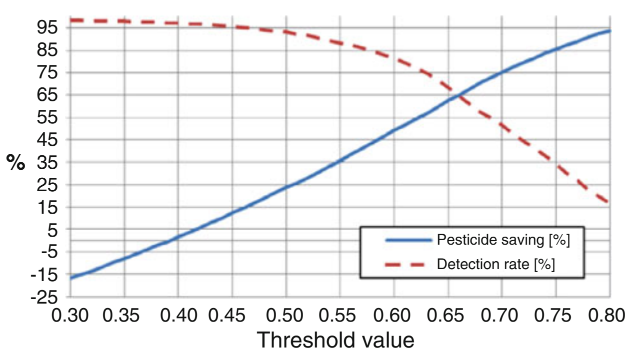

Fig. 12 Optimizing threshold value for GDA1

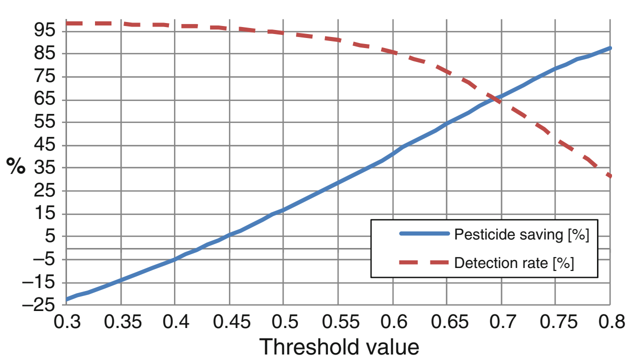

Fig. 13 Optimizing threshold value for GDA2

5.4 Discussion

The use of pesticides reduction as the main parameter to be maximized reflects our main research motivation which is to reduce the amount of pesticides used in modern agriculture. By setting this parameter as the objective function we were able to tune the algorithm such that maximum pesticide reduction is achieved while meeting the desired grape detection rates. In these analyses the minimum grape detection rate was set to be 90% (compatible with farmer's demands); however, this value can be defined by the farmer. When using minimum detection rate of 90% we were able to show a theoretical pesticide reduction of 30% compared to the conventional pesticide spraying method.

In common modern spraying method the farmer sprays a strip of 50 cm. As shown in Fig. 11, some of the grape clusters exceed the strip boundary. As a result, some portion of the grape clusters is not being sprayed. By enlarging the strip width better coverage can be achieved on the expense of pesticide waste. By using the suggested spraying algorithms the farmer can set the desired coverage and the resulted pesticide reduction.

The evaluation of the different GDA3 masks over a set of 100 images indicated that the mask with the largest pesticide reduction is the grape clusters mask (Fig. 7b). Reduction rates for the different masks with a detection rate of 90% are presented in Table 5. The pesticide reduction rate was calculated as the percentage of detected grape area versus the manually marked area.

6 Conclusions

The amount of spraying material can be reduced by 30% while detecting and spraying 90% of the grape clusters. Reductions of 25 and 26% of material can be achieved when using GDA2 and GDA3, respectively. The main innovation of this paper is the approach in which machine vision parameters are optimized by analyzing the actual chemical reduction rates instead of imaging target detection and miss rates which is the common parameter used. Algorithms were tested on images taken in commercial vineyards while sampling a variety of grape species. This will ensure that the future robotic

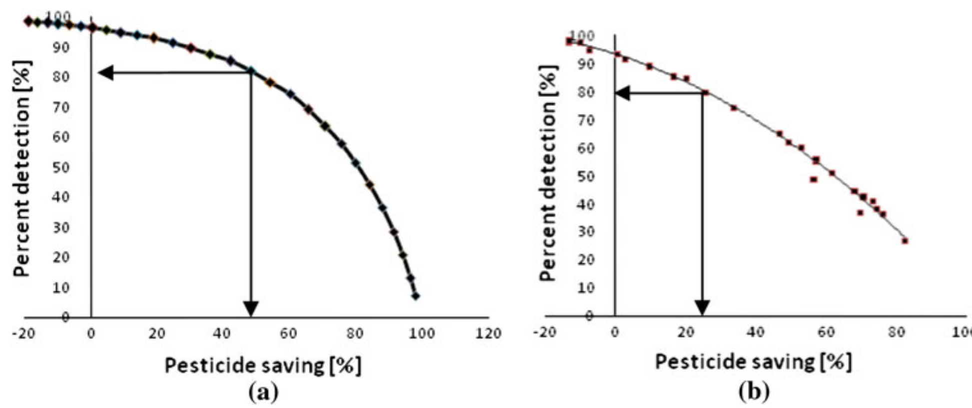

Fig. 14 Relation between detection rate and pesticides reduction. (**a**) GDA1; (**b**) GDA2

Table 4 Robot speed in relation to processing time

Algorithm	Processing time (s)	Maximal robot speed [m/s] (km/h)
GDA1	0.65	3.07 (11.07)
GDA2	1.43	1.39 (5.03)
GDA3	1.15	1.73 (6.26)

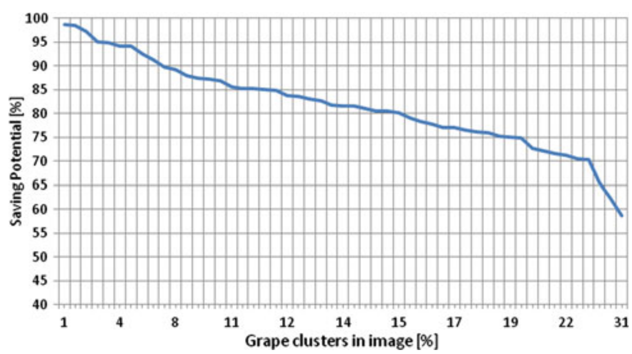

Fig. 15 Relation between *saving potential* and grape clusters in the image

Table 5 GDA3 performance of the four masks

Mask	Detection rate (%)	Pesticide reduction (%)
Grape cluster	90.45	24.08
Center zero	89.95	23.90
Single grape	90.10	22.20
Negative center	90.53	12.73

sprayer will not be limited to certain species. Another important contribution of this work is the establishment of a public available dataset of photos taken in vineyards.

In order to implement these algorithms on an operational robotic sprayer, the algorithm processing time should not

Table 6 Final GDA's performance

Algorithm	Reduction of pesticide agent (%)	Grape as grape **TP** (%)	Foliage as grape **TN** (%)	Grape as foliage **FP** (%)	Processing time (s)
GDA1	30.59	90.4	9.59	73.48	0.65
GDA2	25.58	90.73	9.26	78.73	1.43
GDA3	26.79	90.7	9.67	79.18	1.15

exceed 1.5 s for each image (assuming an average driving speed of 5 km/h).

Ongoing research is dealing with integrating the machine vision algorithms into a robotic sprayer focusing on real-time implementation.

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