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# Human-Robot Cooperative Precision Spraying: Collaboration Levels and Optimization Function

**Ron Berenstein, Yael Edan**

*Dept. of Industrial Engineering and Management*
*Ben-Gurion University of the Negev, Beer-Sheva, 84105*
*Israel (Tel: 050-622-0657; e-mail: berensti@bgu.ac.il).*

**Abstract:** This paper presents two elements for the collaboration of a human operator with a robotic sprayer: definition of human-robot collaboration levels and a spraying coverage optimization function. Four levels of human–robot collaboration for marking the areas to be sprayed are developed and presented. A Spraying Coverage Optimization Function (SCOF) is developed as a utility function that evaluates the profit [$] of the spraying process given the process variables values. The SCOF influencing parameters are classified and presented.

*Keywords:* Human-robot collaboration, spraying, selective spraying, spraying evaluation

## 1. INTRODUCTION

Pesticides are an integral part of the worldwide agriculture. Between 30 and 35% of crop losses can be prevented when harmful insects and diseases are eliminated by spraying pesticides (Cho and Ki, 1999). Although pesticides are needed in modern agriculture, they are poisonous and are dangerous for humans (Dasgupta et al., 2007, Rogan and Chen, 2005) and the environment (Pimentel and Lehman, 1993, Reus et al., 2002).

Developing a target-specific pesticide robot sprayer can reduce the amount of pesticides used in modern agriculture and potentially remove the human from the pesticide spraying process. Studies show that up to 60% of pesticide use can be reduced by using selective sprayers (Elkabetz et al., 1998, Gil et al., 2007, Goudy et al., 2001).

For economic feasibility the robotic sprayer must be able to detect and spray more than 95% of the targets successfully (Blackmore et al., 2001). Despite intensive R&D in detection of agricultural objects, most target detection applications (grapes, apples, tomatoes, oranges, peaches, melons, eggplants, and strawberries) result in only 75–80% detection of targets with a maximum of 90% successful detection noted (Berenstein et al., 2010, Jeon et al., 2005, Lamm et al., 2002). In a spraying application it is important to minimize also the false alarms so as to reduce overall pesticide material and minimize environmental pollution.

In order to overcome this 95% target detection barrier, a human-robot collaboration method was developed under the assumption that improved system performance can be achieved by taking advantage of human perception capabilities. The primary goal of this work is to increase the target detection HIT rate over 95%. A secondary goal is to minimize the False Alarm (FA) detection rate. These goals are expected to be achieved by the collaboration of a human operator with the robotic target detection process.

This paper presents two elements for the collaboration of a human operator with a robotic sprayer: **human-robot collaboration levels** and a **Spraying Coverage Optimization Function** (SCOF). Other elements critical for implementing an operational human-robot collaborative system include the spraying method (Berenstein and Edan, 2012b), interface design (Berenstein et al., 2012) and the marking method (Berenstein and Edan, 2012a) are underway.

Optimal spraying application is defined as a homogenous layer of pesticide applied solely toward the target (grape clusters or foliage). Spraying Efficiency (SE) is calculated by evaluating four spraying attributes: **i**) sum of area sections within the target area that the sprayer missed, **ii**) the amount of pesticide material sprayed outside of the target area, **iii**) the thickness of the spraying layer and **iv**) the spraying homogeneity (achieved by minimizing spraying overlap). The SE depends on several parameters related to the Human Operator (HO), the robotic sprayer, the HO-robot collaboration method and the specific SCOF affecting parameters as outlined in section 4.

The developed methods were applied for a case study of detecting grape clusters in vineyards which is considered a complicated case. Due to the non-uniform and incoherent shape of the grape clusters (as opposed to the uniform round shape of citrus) both the human and the robot must mark the entire areal position of the target (as opposed to solely marking the center of mass in circular objects e.g., citrus, apples).

## 2. HUMAN-ROBOT COLLABORATION LEVELS

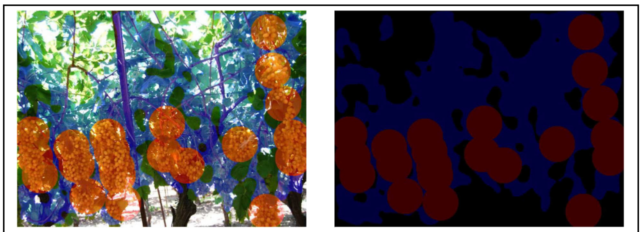
Four levels of human–robot collaboration for target marking have been developed based on Sheridan's 10 levels of human-robot collaboration (Sheridan, 1992) and based on previous work in agricultural target detection (Bechar and Edan, 2003). The motivation of incorporating a human operator in the target marking process is to use the human outstanding perception skills to improve target detection and marking.

**Collaboration level 1 – fully manual human target marking**. The human has a fixed period of time, corresponding to the robot's advance speed along the row, to mark maximum target area with maximum accuracy. Maximum accuracy is defined as maximum target area along with minimum foliage within the marked area (max HIT and min FA). Fig. 1a illustrates the human target marking procedure where the red circles indicate the marked areas. Fig. 1b illustrates the marked image for post analysis (Berenstein and Edan, 2012a).

a b

Fig. 1 - Collaboration level 1, (a) user marked image, (b) image for analysis

**Collaboration level 2 – robot suggests, human approves.** For every captured image the grape clusters are automatically marked using a machine vision algorithm for grape clusters detection (Berenstein et al., 2010). The human receives the robot marked image and has the option to approve or decline the robot marked areas. The human must approve every singulated area in order for the area to be sprayed. After confirming the robot marking areas, the human has the option to manually add areas to be sprayed. Fig. 2a illustrates the procedure where the red circles are the human marks and the blue background is the robot suggestion. Fig. 2b illustrates the marked image for post analysis where the red area represents the human marking and the blue area represents the robot marks.



a b

Fig. 2 - Collaboration level 2, (a) user marked image, (b) image for analysis

**Collaboration level 3 – robot marks, human supervises.** The human receives an image with grape clusters marked by the robot using machine vision algorithms (Berenstein et al., 2010). As opposed to **Collaboration level 2**, the human does not confirm the robot marking. The human has the ability to manually reject robot marking areas and to add areas to be sprayed (Fig. 3).

a b

Fig. 3 - Collaboration level 3, (a) user marked image, (b) image for analysis

**Collaboration level 4 – fully autonomous robot marking.** This collaboration method corresponds to Sheridan's 10$^{th}$ level of automation where the computer decides everything and acts autonomously with no human operations (Sheridan, 1992). With this collaboration level the robot uses machine vision algorithms (Berenstein et al., 2010) to detect the grape clusters and sprays solely the detected areas.

The method in which the human operator marks the targets (e.g., marking the target center with constant/variable diameter, "free hand" marking of entire contour) can significantly influence system performance. Several methods for manually marking the targets by the human have been developed and evaluated in order to achieve efficient manual target marking method (Berenstein and Edan, 2012a). The marking methods consider the relevant parameters affecting the marking process such as the method of pointing out the entire target area, marking time and accuracy.

## 3. SPRAYING COVERAGE OPTIMIZATION FUNCTION (SCOF)

The *Spraying Coverage Optimization Function* (SCOF) is the proposed tool to provide meaningful data about the spraying process. The SCOF is designed in a general form in order to correspond to most existing spraying applications.

The SCOF is defined as a utility function that evaluates the profit [$] of the spraying process given the process parameters values. Additionally, the SCOF will be able to recommend the best combination of system variables and their values (e.g., nozzle type, operating pressure, human-robot collaboration level) enabling the farmer to select them and modify them accordingly.

### *3.1. SCOF analytic formation*

The general form of the SCOF is described as:

*(1)* $V_p = V_H + V_{FA} + V_T$

Where, $V_P$ (Profit) is the overall profit from the spraying process, $V_H$ (Hit) is the profit from spraying the designated area, $V_{FA}$ (False Alarm) is the profit from spraying the background instead of the designated area (foliage instead of grape clusters), $V_T$ (Time) is the profit of the operation time. It should be noted that the SCOF can result in negative profit in which the farmer looses from the specific spraying case.

The profit from spraying the designated area ($V_H$) is described in (2):

$$(2)\quad V_H = A \cdot [p_H \cdot G_H - (1 - p_H) \cdot G_{Miss}] - V_{pesticide} \cdot G_{pesticide}$$

Where, $A$ [ Area ] is the target area, $p_H$ is the system probability of spraying the designated area, $G_H$ [ \$ / Area ] is the profit from spraying the designated area, $G_{Miss}$ is the profit from missing the designated area, $V_{pesticide}$ [ Volume ] is the amount of pesticide used and $G_{pesticide}$ [ \$ / Volume ] is the cost of the spraying material per volume.

The system probability $p_H$ is composed of the probability of target detection procedure and the probability of spraying the designated area as described in (3):

$$(3)\quad p_H = p_{detected} \cdot p_{sprayer\ hit}$$

Where, $p_{detected}$ is the probability that the area will be detected and $p_{sprayer\ hit}$ is the probability that the material to be sprayed will hit the designated area.

The system profit $V_{FA}$ is described in (4):

$$(4)\quad V_{FA} = -A_{FA} \cdot G_{FA}$$

Where, $A_{FA}$ [ Area ] is the area of the false alarm (non-target sprayed area), $G_{FA}$ [ \$ / Area ] is the profit from spraying non designated areas.

The system operational costs are described in (5):

$$(5)\quad V_T = -t_{human} \cdot G_{human} - t_{robot} \cdot G_{robot}$$

Where, $t_{human}$ is the time the human is occupied, $G_{human}$ [ \$ / time ] is the human cost per time unit, $t_{robot}$ is the operating time of the robot, $G_{robot}$ [ \$ / time ] is the robot operational costs per time unit.

The SCOF is constructed from a set of static constants (e.g., $G_H, G_{robot}, G_{pesticide}$) and variables that are situation dependent (e.g., $p_{detected}$ has four optional values depending on the human-robot collaboration level). In order to create a valid function that reflects the outcome profit from the spraying process these parameters must be evaluated.

## 4. SCOF AFFECTING PARAMETERS

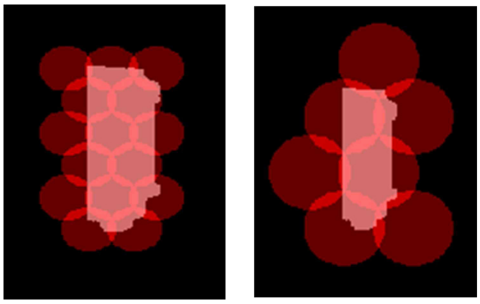
The SCOF affecting parameters are divided into several classes according to their influencing subject.

### *4.1. Sprayer parameters*

Several parameters related to the sprayer mechanization effect the SCOF.

**Pesticide flow rate** is determined by the pesticide layer thickness required to cover the target according to the grower demands. The flow rate can be set by controlling the sprayer pressure and by changing the spraying nozzle orifice. The flow rate affects the SCOF $V_{pesticide}$ value.

**Spray geometry**, the geometric projection of the spray on the target. Traditional sprayers use nozzles with round spray projection. The spray geometry influences the dispersing of the pesticide and the spraying resolution. By using a small diameter round shaped sprayer, the spraying resolution can be higher on behalf of a larger number of sprays per target (e.g., the target in Fig. 4a requires 15 sprays to cover the target while in Fig. 4b only 7 sprays). The spray geometry parameter affects the SCOF $A_{FA}$ value and the $t_{robot}$ value (less number of sprays implies less time to spray the target).



a b

Fig. 4 - Spray diameter, (a) small diameter, (b) large diameter

### *4.2. Robot parameters*

Several parameters as indicated below influence the robot sprayer (Fig. 5) performance.

Fig. 5 - Robotic sprayer (Berenstein et al., 2010)

**Robot target detection**, the robot target detection procedure is based on algorithms developed to detect grape clusters using machine vision (Berenstein et al., 2010). The robot target detection parameter affects the $p_{detected}$ value.

**Robot travelling speed** is the robot movement speed along the vineyard row while performing the spraying procedure. The travelling speed affects the $t_{robot}$ and the $p_{detected}$ value.

**Targeting the nozzle toward the target accuracy**, the spraying nozzle is directed toward the target by using a

Pan\Tilt head (Fig. 6). The accuracy of the pan\tilt head affects the $p_{\text{sprayer hit}}$ value.

a b

Fig. 6 – (a) Pan\Tilt head with spraying nozzle attached, (b) spraying boom with spread nozzles

### *4.3. Human parameters*

This class includes parameters related to the human operator.

**Human expertise** affects the SCOF $p_{\text{detected}}$ value. An expert operator can improve the target detection and marking.

**Human fatigue** affects the $p_{\text{detected}}$ value of the SCOF. The system is able to cope with the operator fatigue by changing the human-robot collaboration levels. However, increasing the collaboration level increases fatigue. In extreme case of human fatigue, a fully autonomous robot marking collaboration level can be applied (level 4).

**Human workload** affects the SCOF $p_{\text{detected}}$ value. In the same manner as the human fatigues, the system is able to cope with the human workload by changing the human-robot collaboration levels.

**Situation awareness** is the comprehension of grape clusters within the image frame. The situation awareness parameter affects the $p_{\text{detected}}$ value.

### *4.4. Human-robot collaboration parameters*

This class summarize the parameters related to the way human operator collaborates with the robot and its effect on the SCOF.

**Areal target marking method**, the target marking process can be applied using several target marking techniques. The target marking technique affects the $p_{\text{detected}}$ value and the $F_{\text{FA}}$ value of the SCOF. In a parallel study three methods of target marking methods were evaluated (Berenstein and Edan, 2012b).

**Collaboration interface** is defined as the way the human interacts with the computer (screen size, touch screen/ stylus pen/mouse). The interface technology and the information display affects the $p_{\text{detected}}$ value and the $A_{\text{FA}}$ value of the SCOF (Berenstein and Edan, 2012a, Berenstein et al., 2012).

### *4.5. Environmental conditions parameters*

**Wind Speed and direction** affects the SCOF $p_{\text{sprayer hit}}$ value. The robot targeting algorithms must consider this parameter in order to precisely direct the pesticides toward the target.

### *4.6. Biological related parameters*

**Pest spread**, the amount of required pesticide is proportional to the pest spread. This parameter affects the $V_{\text{pesticide}}$ value (more pesticides must be sprayed).

**Period during the season parameter**, the size of targets change along the season (the grapes grow during the season). This parameter affects the **Spray Geometry parameter** (small target require small spray diameter and vice versa).

## 5. AUTONOMOUS ROBOT OPERATION PRELIMINARY ANALYSIS

Preliminary analysis is presented for the autonomous robot operation, the fourth collaboration method in which the human is not involved. Hence, the SCOF affecting parameters related to the human can be neglected. In this spraying scenario the robot moves along the vineyard row in step mode (i.e., moves a constant distance → stops → performs the task → moves a constant distance). In each step, the robot captures an image that contains grape clusters. The step length is equal to the captured image width. The images width in this case is approximately 1500[mm] (as a result of the agricultural terrain the distance between the robot and the vineyard row cannot be constant, hence, the images width are not constant).

Fig. 7a is an image capture from a commercial vineyard acquired in Lachish, Israel during the 2010 growing season. The image resolution is 600X800 and the image width is 1500[mm].

a b

Fig. 7 – (a) Vineyard image, (b) Area to be sprayed (257985 pixels)

Pixel dimensions can be calculated as:

$$(6)\quad pixel\,width = \frac{1500}{800} = 1.875[mm]$$

$$(7)\quad pixel\,area = 1.875^2 = 3.5156[mm^2]$$

According to (Berenstein et al., 2010) the $p_{\text{detected}}$ is 90% of the grapes in the image. $p_{\text{sprayer hit}}$ is currently considered to be

100% (on-going experiments are dedicated to evaluate this value).

$$(8)\quad p_{\mathrm{H}} = 0.9 \cdot 1 = 0.9$$

$$(9)\quad A = 257985 \cdot 3.5156 \cong 906972[mm^2] = 0.906[m^2]$$

$$(10)\quad V_{\mathrm{pesticide}} = \frac{A}{10} \cong 0.0906[L]$$

For this case study we assume that it requires 1[L] to cover 10[m$^2$] and that the gain from spraying the target ($G_H$) is 2[\$/m$^2$], the loss of missing target ($G_{MISS}$) is 3[\$/m$^2$] and the gain from false alarm ($G_{FA}$) is 0.5[\$/m$^2$].

$$(11)\quad V_H = A \cdot [0.9 \cdot 2 - (1 - 0.9) \cdot 3] - V_{\mathrm{pesticide}} \cdot 10 = 0.453[\$]$$

According to (Berenstein et al., 2010) approximately 30% of the area detected as targets are False Alarms.

$$(12)\quad V_{FA} = -A * 0.3 * 0.5 = -0.1359[\$]$$

$$(13)\quad V_{\mathrm{T}} = -t_{\mathrm{robot}} \cdot G_{\mathrm{robot}} = -3[\sec] \cdot 10\left[\frac{\$}{h}\right] = -0.008[\$]$$

In (13) we assume that the time required to spray the designated area is 3[sec] and the operational cost of the robot are 10[\$/h]. These values will be investigated in depth in future research.

The overall theoretical gain from spraying Fig. 7a is:

$$(14)\quad V_{\mathrm{p}} = V_{\mathrm{H}} + V_{\mathrm{FA}} + V_{\mathrm{T}} = 0.453 - 0.1359 - 0.008 = 0.309[\$]$$

This case study shows that the profit from spraying the area captured in the image is 0.309\$. Since this value is positive, the SCOF advises the farmer that he will gain from spraying the image using autonomous robot. This result refers to a spraying distance of 1.5m. By normalizing this result to 1m (0.206[\$/m]) and multiplying by the entire vineyard row length, the cost of spraying the entire vineyard can be estimated.

The size of a common vineyard is 50X100[m], the distance between two rows is 3[m] hence, each field contains 17 rows with length of 100[m]. The overall profit from spraying such a field is:

$$(15)\quad \textit{overall profit} = 17 \cdot 2 \cdot 100 \cdot 0.206 \cong 700[\$]$$

**Table 1** summarizes the SCOF sensitivity analysis of three parameters: $p_{\mathrm{detected}}$, $G_H$ and $G_{MISS}$. Results indicate that $G_{MISS}$ has high influence when the target detection rate is low and vice-versa, when the target detection rate is high, the $G_{MISS}$ has low influence. $G_H$ has high influence on the spraying profit. Increasing $p_{\mathrm{detected}}$ strongly effects the profit with an average profit of 500\$ per field spray for 5% improvement of detection.

**Table 1 - Sensitivity analysis for the overall spraying profit**

| $p_{\mathrm{detected}}$ | $G_H = 2$, $G_{MISS} = 3$ | $G_H = 1$, $G_{MISS} = 3$ | $G_H = 1$, $G_{MISS} = 1$ | $G_H = 2$, $G_{MISS} = 2$ | $G_H = 3$, $G_{MISS} = 1$ |
|---|---|---|---|---|---|
| 0.7 | -1355 | -2794 | -1560 | -738 | 1317 |
| 0.8 | -327 | -1971 | -1149 | 86 | 2139 |
| 0.85 | 186 | -1560 | -944 | 495 | 2550 |
| 0.9 | 700 | -1149 | -738 | 906 | 2962 |
| 0.95 | 1214 | -738 | -532 | 1317 | 3373 |

By using the same set of equations [(9), (10), (11), (12), (13)] for estimating the farmer gain from spraying the entire field regardless of the grape clusters positions (16), we reveal a farmer loss (17).

$$(16)\quad V_{\mathrm{p}} = V_{\mathrm{H}} + V_{\mathrm{FA}} + V_{\mathrm{T}} = 0.124 - 0.390 - 0.008 = -0.274[\$]$$

$$(17)\quad \textit{overall profit} = 17 \cdot 2 \cdot 100 \cdot 0.274 \cong -931[\$]$$

The farmer loss from not spraying anything in the field (and not operating the robot) is [(18), (19)]:

$$(18)\quad V_{\mathrm{p}} = V_{\mathrm{H}} + V_{\mathrm{FA}} + V_{\mathrm{T}} = -0.271 - 0 - 0 = -0.271[\$]$$

$$(19)\quad \textit{overall profit} = 17 \cdot 2 \cdot 100 \cdot 0.271 \cong -921[\$]$$

## 6. CONCLUSIONS AND FUTURE WORK

Improved target detection can be achieved by integrating a human with the robot. This paper presented two elements for implementation and evaluation of a human-robot cooperative sprayer.

Preliminary results indicate that the farmer's loss from spraying the entire field is greater than when not spraying the field at all. This conclusion is based on estimated gain values that will be investigated in depth in future research.

On-going experiments (Berenstein and Edan, 2012a) aim to evaluate the $p_{\mathrm{detected}}$ values for the first human-robot collaboration level. These experiments include evaluation of humans marking grape cluster targets with two optional robot traveling speeds.

Future work will also include detailed evaluation for all effecting parameters and collaboration levels similar to Bechar et al. (2007). This will be conducted in simulation, and in both lab and field experiments using the vineyard spraying robot (Berenstein et al., 2010). Additionally, optimization techniques will be used in order to find the best parameters combinations.

## 7. ACKNOWLEDGMENTS

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