Evaluation of Marking Techniques for a Human-Robot Selective Vineyard Sprayer

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Abstract

A human-robot interface was designed for a target-specific pesticide robotic sprayer developed to reduce the amount of pesticides applied. This paper presents three techniques for marking targets in the remote interface. The assumption is that collaboration of a human operator with a robotic system can increase target detection rate and decrease false alarm rate. The human task is to mark the targets, defined as the grape clusters. Three techniques of target marking were developed and evaluated: (**i**), the operator marks the center of a constant diameter circle. The operator can mark multiple circles for each target. (**ii**), the operator marks a changeable size ellipse. The operator can mark multiple ellipses for each target. (**iii**), the operator free handedly marks the target contour. Experiments were conducted to evaluate the effect of the marking methods on the target detection HIT, FA (False Alarm) and MISS rate. 76 students participated in an experiment in which each student evaluates the three marking methods. Experimental results show that in order to maximize the target detection HIT rate, the best marking method is the constant diameter method which produced 94% HIT rate. The preferable marking method to minimize FA is marking the clusters by free hand.

Key words: HRI, robotics, user interface design.

1. Introduction

Reducing the use of pesticides is a major motivation in the field of precision agriculture. Studies indicate that pesticides can be reduced up to 60% by using selective robotic sprayers (Elkabetz et al., 1998; Gil et al., 2007; Goudy et al., 2001).

Current robotic systems cannot cope with unexpected situations encountered in the unstructured and changing agricultural environment (Edan et al., 2009). Detection of natural objects is especially problematic due to the inherent high variability in shape, texture, color, size, and position (Kapach et al., 2012). This, as well as the limitations of sensor technologies and the changing environmental conditions (e.g., lighting, occlusion, relative humidity), prohibits the use of completely autonomous systems in such environments. Humans, on the other hand, can easily fit themselves into such changing environments due to their perception skills. By taking advantage of the human perception skills and the robot's accuracy and consistency a combined human-robotic system can be simplified and result in improved performance (Fong and Thorpe, 2001).

This work is part of a larger project focusing on development of a vineyard site specific sprayer (Berenstein, 2010; Berenstein and Edan, 2012; Berenstein et al., 2012; Berenstein et al., 2010).The main project motivations were to reduce: (**i**) the use of pesticide by selectively spray the grape clusters, (**ii**) the amount of working hands and (**iii**) human exposure the pesticides. Grape clusters detection algorithms developed were able to detect up to 90% of the targets (Berenstein et al., 2010). However, for economic feasibility the robotic sprayer must be able to detect and spray more than 95% of the targets successfully (Blackmore et al., 2001). 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 focus of this current work is to develop and compare different human target marking methods for the robotic system. Three target marking methods are compared for two robot speeds. Experiments with 76 participants were conducted; in each experiment each participant evaluated three marking methods for one robot speed.

2. User interface

The user interface is designed to allow a human to remotely collaborate with a robot in a target detection process. The use of the interface will allow human working place flexibility (e.g., home, office, field) since the communication between the robot and the interface is WEB based and hence can be accessed from any remote location. Furthermore, it will increase detection rates. By separating the human from the robotic sprayer human exposure to pesticides is reduced.

A semi-continuous working procedure (FIGURE 1) was designed for the human-robot collaborative work. The robot autonomously and continuously advances along the vineyard row. The spaced interval between images is derived according to the captured image width.

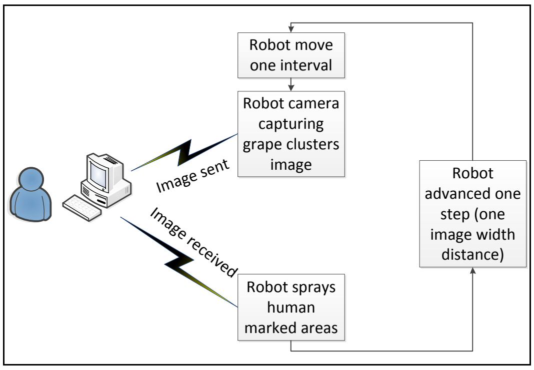

FIGURE 1 - Spraying system working procedure

2.1. Target marking methods

Three target marking methods were evaluated: (**i**) **circle with constant diameter**, the operator sets the center of a constant diameter circle and by clicking the mouse left button the circle is marked on the image (FIGURE 2a). Using this method, the operator cannot change the circle diameter. (**ii**) **ellipse with changeable size**, by clicking the mouse left button (without release) the user sets the ellipse starting point, and at the point of releasing the mouse left button the end point of the ellipse is set (FIGURE 2b). (**iii**) **free hand marking**, the operator clicks the left mouse button (without release) and surrounds the target area. When releasing the mouse button the area bounded is marked as target (FIGURE 2c).

In each method the area bounded within the marked area is considered as “detected” and colored in red. While using each of the marking methods, the operator can use the right mouse button for erasing a marked target. The erasing method is identical to the marking method (e.g., when using the constant circle diameter method, the operator can click the right mouse button and the target marked within that area will be erased).

When the target marking process is completed (due to marking all the targets or end of marking time for the image) a binary image is saved for post-analysis (FIGURE 2d,e,f).

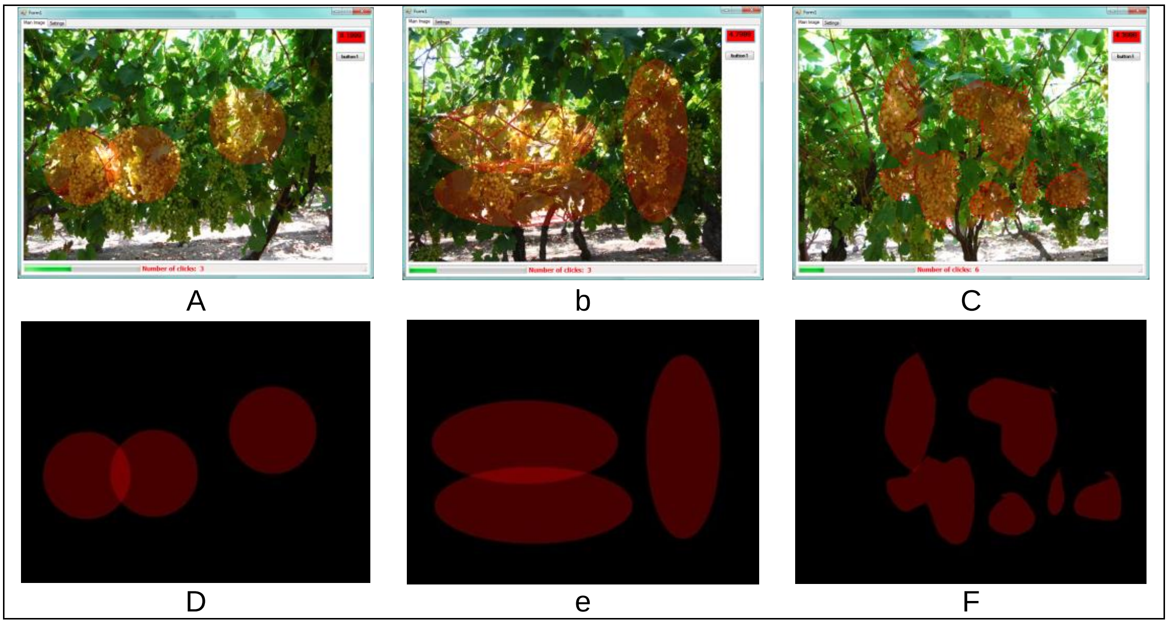

FIGURE 2 – Marking methods. (a) constant diameter circle, (b) ellipse, (c) free hand, (d) constant diameter circle result, (e) ellipse result and (f) free hand result

2.2. User interface design

The user interface was developed under .NET environment using C# language. The interface is based on WIMP (Windows, Icons, Menus and Pointers). The user interface contains two main windows, management and target marking (FIGURE 3).

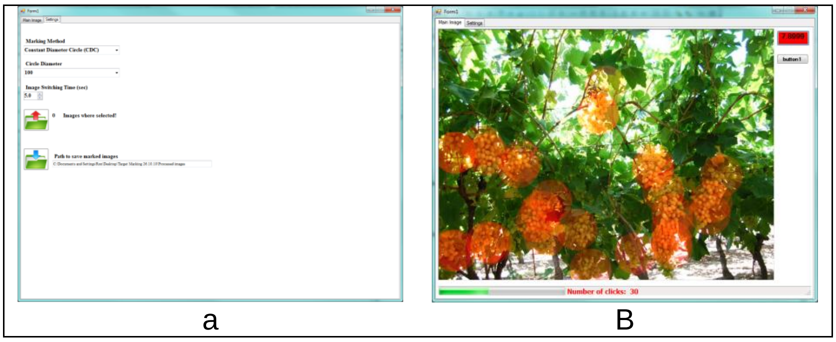

FIGURE 3 – user interface. (a) manegment window, (b) target marking window

3. Methods

Performance measures were set as the target HIT rate (the percentage of grape clusters marked) and FA (false alarm) rate (the percentage of background that was marked incorrectly as target). Two preliminary experiments and a single main experiment were conducted in order to evaluate the three target marking methods for two robot speeds.

An image database for the experiment was created with 129 RGB images with resolution of 600x800. The images were captured in a commercial vineyard in Lachish, Israel during the 2009 growing season. The ground truth position of the grape clusters were marked by three experts. Each expert had unlimited time to mark all the targets in each image. Target marking was performed by free hand using Windows Paint software. Due to the natural disagreement between the experts a majority judge rule was applied to set the ground truth position of the targets (i.e., pixels marked by two or more experts were considered as target).

3.1. First preliminary experiment – evaluate the diameter for the first target marking method

The experiment was conducted to evaluate the optimal diameter for the first target marking method (constant diameter circle). The performance measures for the experiment were the number of mouse clicks per image, the FA rate*(1)* and the HIT rate(*2)*. The experiment objectives were to minimize the number of mouse clicks, minimize the FA rate and maximize the HIT rate. The experiment objectives were explained to the users. Two participants were taken for the experiment and were allowed to mark the images without time limit. Each participant marked 129 images with 7 different circle diameters (70 to 100mm with 5mm interval). Experimental results indicated that the optimal circle diameter is 90mm according to the performance measure (Dichter and Cohen, 2011).

$$(1)\quad FA[\%] = \frac{\text{number of pixels falsely marked as target}}{\text{total number of pixel in the image } (600*800)} * 100$$

$$(2)\quad HIT[\%] = \frac{\text{number of marked pixels that are part of the designated target}}{\text{total pixel number of the designated target (ground truth)}} * 100$$

3.2. Second preliminary experiment – evaluating the operator learning curve

Learning is defined as the amount of time required for a group of people without experience and without interface acquaintance to reach satisfactory use of the interface (Norman, 1988). This experiment aimed to evaluate the amount of time required for a new interface user to learn the interface and reach adequate target marking skills. Interface learning effect can be prevented when providing the participants with the sufficient learning time.

Twenty engineering students in the ages of 23~30 participated in the experiment (Dichter and Cohen, 2011). Each participant marked 50 images with image switching time of 12 seconds. The participants were asked to mark the grape clusters in the image using the constant circle diameter method.

Experimental results indicated a strong relation between the image sequence and the HIT rate (FIGURE 4). The minimal target marking limit was set to 90%. FIGURE 4 shows that at image number 20 the participants crossed the 90% barrier. Since the image switching time was 12 seconds, the learning time was set to 4 min ($t = 12*20 = 240[s] = 4[\min]$).

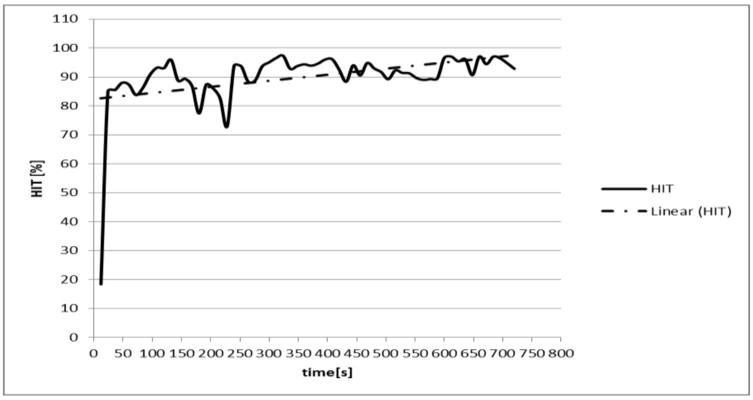

FIGURE 4 – learning curve

3.3. Main experiment

The main experiment simulates target marking by a human from a remote location. The participant had to mark the targets for the robot to spray. The experiment goal was to determine the best marking method for two different robot speeds. 72 engineering students in the ages of 23 ~ 30 participated in the experiment. A set of 129 images were presented to the participants. The participant task was to mark the grape cluster using the marking method assigned for the image set. Each participant evaluated the three marking methods while experiencing one of two robot speeds (set as 12 and 15 seconds corresponding to XX km/h advance of the robot along the row). The performance measures were defined as HIT, FA, CR(*3)* and MISS(*4)*.

$$(3)\quad CR[\%] = \left(1 - \frac{\text{number of pixels falsely marked as target}}{\text{total number of non-target pixels}}\right)*100$$

$$(4)\quad MISS[\%] = 100 - HIT$$

4. Results and conclusions

Experimental results (FIGURE 5) reveal that the best HIT rate was obtained while using the constant diameter circle marking method for both the slow and fast robot speeds. Using the slow robot speed increases the HIT rate value from 91% to 94%. When there is high importance for HIT rate and less importance for FA then the recommended marking method is the **constant diameter circle**. For applications that require low FA rate, the free hand marking method yields best results (19.1% FA for the slow robot speed).

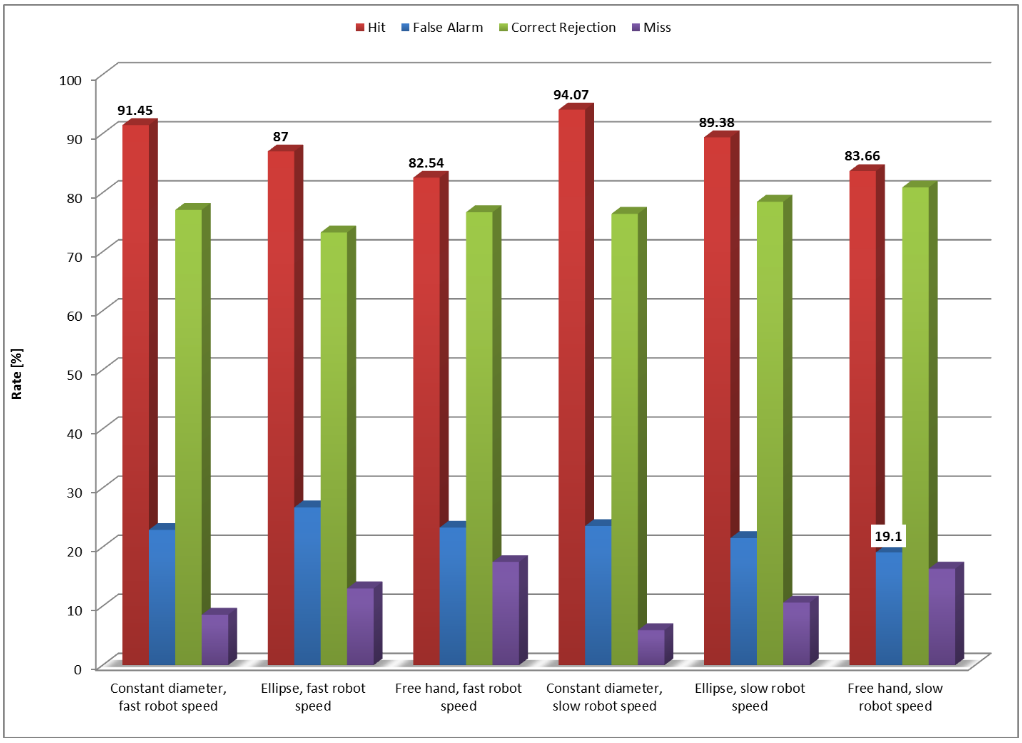

FIGURE 5 - Main experiment results

The preferable marking method is task dependent. For tasks with high importance on HIT rate the best marking method is the constant diameter circle (for both robot speeds). Tasks with high importance on the FA rate are recommended to use the free hand marking method. Slow robot speeds increase the target detection HIT rate and decrease the FA rate, as expected (since the user has more time to spend on each image). Naturally, using a slower robot speed increases the farm expenses (higher robot operation time, more labor hour) and hence this should be evaluated from a cost/benefit aspect.

This work focuses on the first level of human-robot collaboration, fully manual target detection, according to Sheridan (1992). Ongoing work is experimenting performance of different levels of human-robot collaboration. In addition, we are developing a *Spraying Coverage Optimization Function* (SCOF) which is the proposed tool to provide meaningful data about the spraying process. The SCOF will provide an economic evaluation of the spraying process. The function will evaluate the profit [$] of the spraying process given the process variables values (e.g., robot speeds, detection rates).

5. Acknowledgements

This research was partially supported by the Paul Ivanier Center for Robotics Research and Production Management, and the Rabbi W. Gunther Plaut Chair in Manufacturing Engineering, Ben-Gurion University of the Negev.

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