On-line trajectory planning for autonomous spraying vehicles

Pablo Urcola[1], Tom Duckett[2], and Grzegorz Cielniak[2]

[1] University of Zaragoza, Spain, urcola@unizar.es
[2] University of Lincoln, UK, {gcielniak,tduckett}@lincoln.ac.uk

Abstract. In this paper, we present a new application of on-line trajectory planning for autonomous sprayers. The current generation of these vehicles use automatic controllers to maintain the height of the spraying booms above the crop. However, such systems are typically based on ultrasonic sensors mounted directly on the booms, which limits the response of the controller to changes in the terrain, resulting in a sub-optimal spraying process. To overcome these limitations, we propose to use 3D maps of the terrain ahead of the spraying booms based on laser range-finder measurements combined with GPS-based localisation. Four different boom trajectory planning solutions which utilise the 3D maps are considered and their accuracy and real-time suitability is evaluated based on data collected from field tests. The point optimisation and interpolation technique presents a practical solution demonstrating satisfactory performance under real-time constraints.

Keywords: trajectory planning, outdoor mapping, agricultural sprayers

1 Introduction

The aim of agricultural robotics is to enable automated operation of different farming processes by developing robust and autonomous agricultural vehicles. These intelligent machines will perform tasks like ploughing, spraying or harvesting autonomously with minimal intervention from a human user. This work is concerned with enabling autonomy for horizontal boom sprayers (see Fig. 1). The modern generation of these vehicles feature adjustable spraying booms which can be automatically controlled to maintain a constant distance from the crop. This is a critical process as the height of the boom affects the amount and distribution of the sprayed substance. The current boom control systems rely on boom-mounted ultrasonic sensors for measuring the height and level of the booms. The ultrasonic sensors, whilst inexpensive, are relatively slow and provide noisy information for only a small patch of the terrain immediately below the spraying boom. This results in a sub-optimal spraying process and also restricts the maximum speed of the sprayer, since only a reactive control strategy is possible.

This paper investigates a control system based on alternative sensing technology employing laser range-finders (LRF) and predictive terrain modelling

Fig. 1: Horizontal boom sprayer.

enabling a longer "look-ahead". The core component of the proposed system is a local 3D map of the terrain, reconstructed from a scanning laser range-finder and precise pose information provided by GPS and IMU sensors. With this approach the terrain is sensed in advance, so that the trajectory planner and controller have more time to adjust the height of the booms. The approach not only improves the control accuracy but can also enable new applications such as terrain-based vehicle steering or variable-rate spraying, leading towards development of fully autonomous spraying vehicles. The initial results demonstrating the feasibility of the laser-based mapping in the proposed scenario were presented in [5]. In this work, we extend the approach by presenting on-line trajectory planning for the boom controller.

2 Related Work

Recent advances in agricultural robotics have resulted in a number of robotic prototypes for various scenarios and different stages of plant production. Examples include autonomous robots designed for operations involving spraying [10], mechanical weeding [9], crop scouting [1], etc. Robotic applications in agriculture can bring numerous economic, societal and environmental benefits (e.g. reduced production costs, more friendly working environments, reduced contamination risks, etc.) [8]. However, the future development of such systems will have to address several challenges arising from the complexity of farming processes, outdoor environments, and the mechanics and physical size of agricultural machinery.

Two important challenges addressed in our work are related to 3D mapping and on-line trajectory planning. So far, the majority of outdoor mapping applications consider urban environments (e.g. [6]) where there are physical, man-made structures which assist in the registration of 3D scans, improving the quality of the resulting maps. The existing on-line trajectory planning solutions for mobile robots were mostly applied to vehicle navigation (e.g. [2]) whilst the majority of planning solutions for agricultural machinery consider coverage path planning solutions (e.g. [7]) for subsequent use by GPS-enabled auto-steering systems. In contrast, our work concentrates on the novel application of laser range-finder sensing, combined with GPS and IMU information, to build a scrolling 3D model of the terrain/crop and an on-line planning solution which can be used for improving the control of the sprayer booms (see Fig. 1).

3 Methodology

3.1 System Overview

The main components of the horizontal boom sprayer consist of a spraying vehicle and an adjustable spraying boom which can be folded and unfolded for easier transportation and storage. The length of the booms depends on the sprayer model and ranges from 12 to 18 meters on each side of the vehicle. The proposed laser-based boom controller uses information from the following sensors:

- a GPS receiver (Trimble) providing global position measurements at a regular rate of 4Hz. The GPS operates in a differential mode, thus achieving a theoretical accuracy of a few centimetres;
- an IMU (Xsens MTi-30) providing 3D orientation measurements based on the information from the integrated accelerometer, gyroscope and magnetometer, at rates up to 100Hz;
- an outdoor laser range scanner (Hokuyo UTM-30LX-EW) providing 2D distance information covering 270° field of view and 30 m range. For each measurement, up to 1080 points are obtained at a frequency of 40 Hz;
- sprayer's telemetry, providing information about the current boom configuration through the internal CAN bus.

All these components are connected to a laptop with an Intel CORE i7 processor running Ubuntu and Robot Operating System (ROS). GPS, IMU and laser sensors are attached to the front of the vehicle so that a map of the height of the terrain/crop can be built and used to dynamically control the configuration of the movable booms to reach the optimal spraying height. The whole system is divided into four interrelated processing components including localisation, map building, trajectory planning and controller, as shown in Fig. 2. The main contribution presented in this paper is the on-line trajectory planning component.

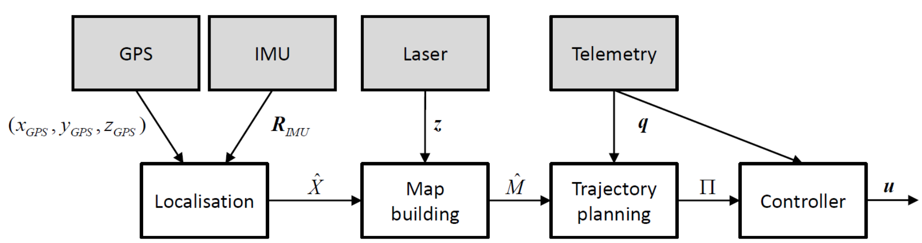


Fig. 2: System overview.

3.2 Self-localisation and Mapping

The self-localisation component computes the best estimation of the position and attitude of the vehicle $X = (x, y, z, R)$ from data provided by the GPS and IMU sensors. To estimate X we are using a Kalman Filter approach which combines GPS and IMU measurements $\boldsymbol{x} = (x_{GPS}, y_{GPS}, z_{GPS}, R_{IMU})$ together with a motion model $f()$ (a constant speed model in our case) using the following formula:

$$\hat{X}(t + \Delta T) = f(\hat{X}(t)) + K(t)\left(\boldsymbol{x}(t) - h(f(\hat{X}(t)))\right). \tag{1}$$

The weighting factor $K(t)$ is computed using the Kalman Filter equations, ΔT is the discretisation step and $h()$ is the measurement function that relates the GPS and IMU data $\mathbf{x}$ to the estimation $\hat{X}$.

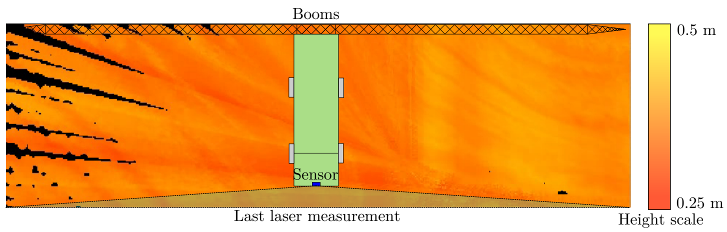
Thanks to the precise localisation estimate obtained from the self-localisation component, the mapping component can compute the position of laser points in 3D coordinates. By accumulating laser measurements $\boldsymbol{z} = (z_0, \ldots, z_k)$ while the vehicle is moving, it is possible to build a local 3D representation corresponding to the crop canopy/terrain. To avoid excessive memory and computational requirements related to 3D point clouds, we use a height map $\hat{M}$ which approximates the ground surface by using a 2D discrete grid. As the vehicle moves around the field, the rolling map is updated. The size of $\hat{M}_{n\times m}$ depends on the length of the boom (n) and the length of the vehicle (m). Each cell in the grid stores the height of the canopy at that position (see Fig. 3). The quality of the map is further enhanced by spatial smoothing which eliminates some of the smaller gaps in the map. We also store the average height value of all the points projected into a cell together with their number, which is used as a confidence measure. This confidence value is used for spatial smoothing but also by the planner presented in the following section.

3.3 Trajectory Planning

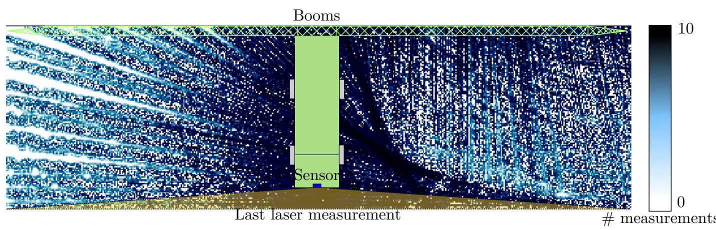
The trajectory planner is responsible for computing an optimal boom trajectory based on the 3D map provided by the mapping component. The trajectory $\Pi(t)$ is a sequence of configurations $\boldsymbol{q}_1, \ldots, \boldsymbol{q}_m$ which best fit the map surface whilst being feasible and safe. The boom is attached to the vehicle by its middle part. The left and right booms are connected to the middle by two joints. The whole boom can be moved up and down, tilt around the central point and also, each of the side can be folded with respect to the middle part. Thus, the boom has four joints whose position defines the configuration $\boldsymbol{q} = (d, \theta, \alpha_r, \alpha_l)$, as shown in Fig. 4. We define the size of $\boldsymbol{q}$ as r (= 4 in our case).

To evaluate the fitness of a particular boom configuration, we consider the average distance from the boom to the crop/terrain and compare it with the desired spraying distance H. Consequently, we define the *score* of a configuration as

$$score(\boldsymbol{q}) = \frac{1}{2}\sum_{i=1}^{n}\left(height(y_i, \boldsymbol{q}) - (\hat{M}(y_i) + H)\right)^2, \tag{2}$$



(a) The height map. Black pixels represent cells without measurements.



(b) The information map representing the number of measurements.

Fig. 3: Top view of the sprayer projected on the height and information maps when the vehicle is turning.

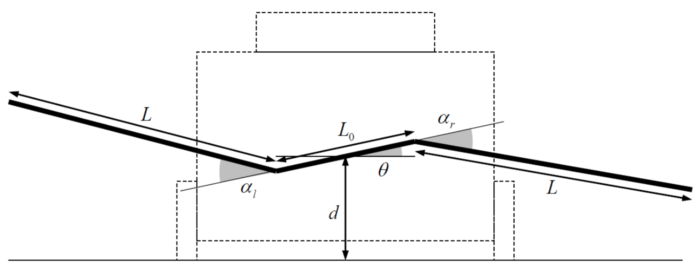


Fig. 4: Boom configuration viewed from the rear of the vehicle.

where $height()$ is the height of the point y of the boom given a configuration $\mathbf{q}$ which can be calculated as:

$$height(y; \boldsymbol{q}) = \begin{cases} d - \frac{L_0}{2} sin\theta + (y + \frac{L_0}{2}\cos\theta)\tan(\theta - \alpha_l), & y < -\frac{L_0}{2}\cos\theta \\ d + y\tan\theta, & |y| < \frac{L_0}{2}\cos\theta \\ d + \frac{L_0}{2}\sin\theta + (y - \frac{L_0}{2}\cos\theta)\tan(\theta + \alpha_r), & y > \frac{L_0}{2}\cos\theta \end{cases} \tag{3}$$

To take into consideration the dynamics of the booms so that the trajectories are smooth enough, we introduce a damping term that penalises variations along the trajectories:

$$damping(\boldsymbol{q}_t) = (\boldsymbol{q}_t - \boldsymbol{q}_{t-1})^T \, W \, (\boldsymbol{q}_t - \boldsymbol{q}_{t-1}) \,, \tag{4}$$

where W is a weighting matrix responsible for setting a trade off between smoothness and spraying distance. As a result, for the whole trajectory $\Pi(t)$ consisting of m configurations, we need to find rm different values.

Constraints. To guarantee the feasibility and safety of the trajectory, the trajectory planner must satisfy a set of constraints:

– Initial configuration: the trajectory must start in the current configuration of the boom because it will be sent to the controller as soon as it is computed: $\boldsymbol{q}_0 = \boldsymbol{q}_{curr}$. The number of constraints needed to satisfy this condition is r.
– Configuration limits: values of any configuration $\boldsymbol{q}_i$ are bounded by the lower and upper limits in the configuration space: $\boldsymbol{q}_{min} \leq \boldsymbol{q}_i \leq \boldsymbol{q}_{max}$, resulting in $2rm$ constraints.
– Speed limits: The speed of the booms is also limited. This restriction constrains the possible values for a configuration depending on the previous one in the sequence: $\Delta\boldsymbol{q}_{min} \leq \boldsymbol{q}_{i+1} - \boldsymbol{q}_i \leq \Delta\boldsymbol{q}_{max}$. Similarly to configuration limits, this condition results in additional $2rm$ constraints.
– Safety constraints: to guarantee a safe trajectory, the booms must always be above the surface of the canopy: $h(y_j; \boldsymbol{q}_i) > \hat{M}(y_j)$. This condition must be met for each cell of the map $\hat{M}$ which results in additional mn constraints.

In summary, the full problem requires finding rm optimal values under a set of $r + m(4r + n)$ constraints.

Optimisation solutions. To tackle the problem of constrained optimization we apply first the well-known techniques (i.e. full numerical and discrete combinatorial optimisations) and demonstrate their deficiencies when it comes to practical implementations and then two alternative hybrid solutions (safety planning & local optimisation, and point optimisation & interpolation) that bring the proposed solution to real-time performance at the cost of sub-optimal accuracy.

Full numerical optimisation: This approach tries to find the optimal values for the whole trajectory at the same time while considering the constraints. It is based on an iterative approach which starting from a candidate trajectory looks for a better one while the constraints are still satisfied. In our approach, we consider the penalty and barrier methods. Both methods add an artificial term $g(\boldsymbol{q}_t)$ representing the constraints to the objective function:

$$\Pi(t) = \underset{\boldsymbol{q}_1,\cdots,\boldsymbol{q}_m}{\arg\min} \sum_{t=1}^{m} score(\boldsymbol{q}_t) + damping(\boldsymbol{q}_t) + \gamma_k g(\boldsymbol{q}_t). \tag{5}$$

The penalty weight γ_k is updated at each iteration k until convergence. The penalty method penalises solutions outside the constraints by increasing the score if a particular constraint is not satisfied. However, the procedure can get stuck if the shape of the objective function presents local minima. The second approach, defines a barrier function which has a vertical asymptote at every limit of the constrained set of solutions. This fact makes mandatory that all the considered solutions must be inside the valid set until convergence, requiring small step sizes and resulting in slow convergence.

Discrete combinatorial optimisation: This approach considers only a limited set of values for each variable for optimisation and selects the best one based on the associated score value. In each step, only feasible and safe configurations are considered for evaluation, which ensures satisfying all the constraints. This approach is similar to the Dynamic Window Approach [3] if we consider each step of the trajectory. The greedy solution obtained from DWA is not enough to avoid deadlocks, however, which makes it necessary to consider every possible trajectory. The number of possible configurations grows exponentially with the length of the trajectory making this approach impractical even for very short sequences.

Safety planning and local optimisation: This approach reduces the size of the problem by dividing configuration variables into two types. The height of the whole boom is used to compute a safe trajectory over the canopy. For each row, the average height is set to the desired spraying distance. In the cases where the canopy is higher than the desired height, then the booms are raised to the minimum safe value. The rest of the parameters - tilt and incline angles - are set to accurately resemble the actual shape of the canopy, while the other constraints are satisfied. The approach relies mainly on the height variable and therefore always results in safe trajectories which are, however, not optimal.

Point optimisation and interpolation: The characteristics of the booms including their very limited speed and typically smooth surface of the canopy, allow for optimisation of only a few selected points along the trajectory which is interpolated between the points. The safety and feasibility constraints are considered along the whole trajectory but, due to a large distance between the optimised points, the constraints are easier to satisfy. Some feasibility problems might appear if the canopy is not as smooth as expected, making it impossible to find a feasible interpolation among the points.

4 Experiments

To evaluate the performance of the presented planning solutions, we collected sensory data while the vehicle was driven on a field with short stubble (see Fig. 1) traversing a total distance of 290m, gathering around 4.5M laser measurements together with GPS and IMU data. The spraying vehicle featured 32m long booms and a setup with 10m between the sensor and the booms. We have also introduced a set of virtual obstacles of different size and location (see Fig. 5).

4.1 Results

Due to the prohibitive computational requirements for full numerical and discrete combinatorial optimisations we only present detailed accuracy analysis for the two practical methods. Fig. 7a presents the average error between each configuration and the desired spraying distance calculated by both methods. The local optimisation technique raises the whole boom platform even if a small obstacle is present, increasing the distance from each point on the boom to the canopy. In contrast, the point optimisation method relies on all configuration variables

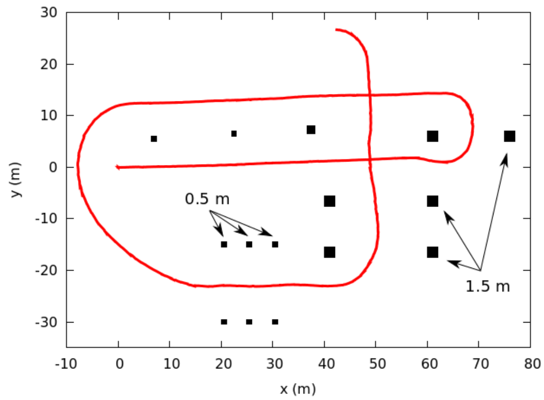
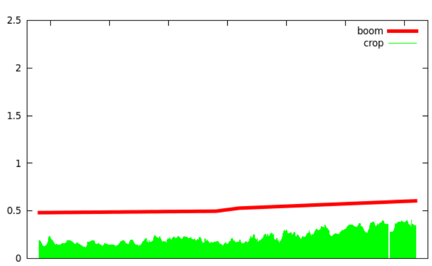
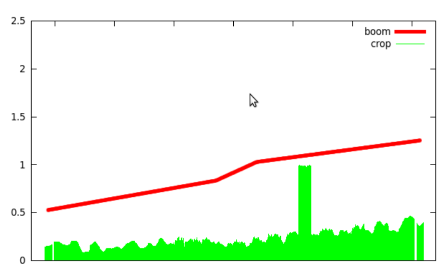


Fig. 5: Dataset used in the experiments: the layout of virtual obstacles (black rectangles) and vehicle trajectory (red line).

and thus the height of the boom is not used as much as in the first method and results in superior performance. The differences in the use of the height variable when negotiating obstacles for both methods are shown in Fig. 7b. Figure 7c and 7d present values of all configuration variables for both methods. It is remarkable that because of the different use of the height variable in both methods, the other configuration components behave completely differently. On one hand, as the height value forces the whole boom to move above the obstacles in the safety planning method, the boom angles are set down so that the distance to the canopy is reduced. On the other hand, the point optimization method does not set the height above the obstacles so that the other variables are still required to guarantee the safety, setting the angle values to increase the height of the boom. Fig. 6 illustrates selected boom configurations for different situations obtained with the point optimisation method.

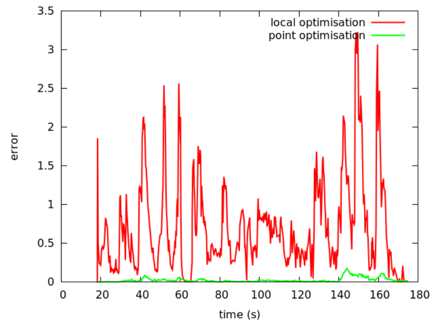


(a) No obstacles.

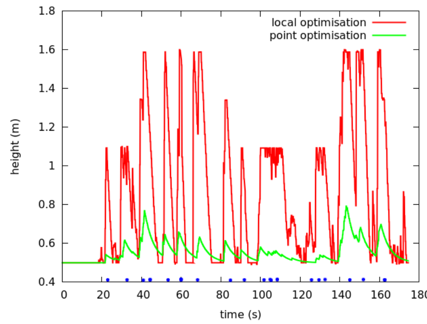


(b) 1m tall obstacle.

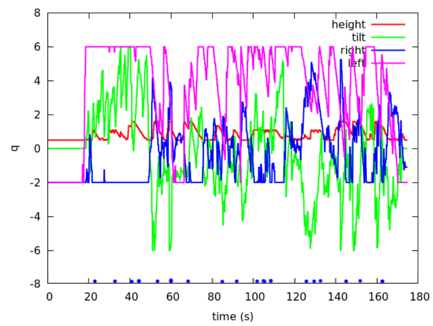
Fig. 6: The point optimisation method - example boom configurations.



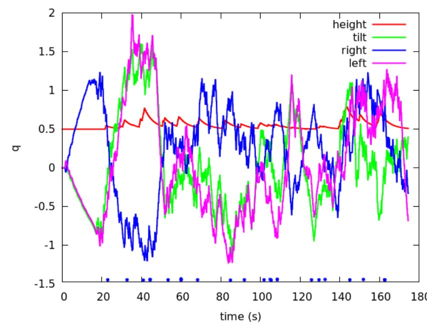
(a) Average error.



(b) Boom platform height.



(c) Configuration variables: safety planning & local optimization.



(d) Configuration variables: point optimization.

Fig. 7: Our results: blue dots indicate the presence of virtual obstacles.

We have also assessed real-time suitability of each proposed planning method. Table 1 presents the time required to calculate a single trajectory by each method for different size of the map (Map 1: $m = 10$, Map 2: $m = 200$). In both cases, the width of the map is the same ($n = 640$). The full numerical optimisation is unable to obtain feasible solutions even for different step size values, and fails due to the presence of local minima. The discrete combinatorial method suffers from the curse of dimensionality and is very slow (i.e. taking hours) even for very small maps. Both of the practical methods proposed are fast enough to be used in on-line applications as they can process several maps a second. The point optimization method method is more than two times slower than the safety planning because the optimization is performed in the full configuration space.

5 Conclusions

In this paper, we propose on-line trajectory planning for autonomous sprayer vehicles. Using the localisation information obtained from GPS and IMU measurements and the observations from the laser range scanner we propose a mapping system to represent the height of the crop canopy ahead and around the

Method	Map 1	Map 2
Full numerical	Out of bounds	Out of bounds
Discrete combinatorial	2 hours	> 12 hours
Safety planning	4 ms	90 ms
Point optimization	8 ms	220 ms

Table 1: Computational time required by the planning methods on an Intel CORE i7 processor.

spraying vehicle. The popular (i.e. optimal) planning methods have been analysed and discarded as they are not suitable for the problem considered. The two practical methods have been evaluated on real data gathered from a spraying vehicle and augmented with virtual obstacles to stress the characteristics of the methods presented. Future work will consider the problems arising from high dimensionality of the state space which might be addressed by using randomised planning methods such as Rapidly-exploring Random Trees [4]. In the current form, a trajectory is computed from scratch when a new map is provided. It will be interesting to take advantage of previous computations to calculate new trajectories. The future system will also combine trajectory planning for both the boom platform and the spraying vehicle.

References

1. Biber, P., Weiss, U., Dorna, M., Albert, A.: Navigation system of the autonomous agricultural robot “BoniRob”. In: Proc. IROS Workshop on Agricultural Robotics (2012)
2. Dolgov, D., Thrun, S., Montemerlo, M., Diebel, J.: Path planning for autonomous vehicles in unknown semi-structured environments. The International Journal of Robotics Research 29(5), 485–501 (2010)
3. Fox, D., Burgard, W., Thrun, S.: The dynamic window approach to collision avoidance. Robotics an Automation Magazine 4(1), 22–33 (1997)
4. LaValle, S.M., Kuffner, J.J.J.: Randomized kinodynamic planning. Journal of Field Robotics 20(5), 378–400 (2001)
5. Moreno, F.A., Cielniak, G., Duckett, T.: Evaluation of laser range-finder mapping for agricultural spraying vehicles. In: Towards Autonomous Robotic Systems (TAROS) (2013)
6. Nüchter, A., Lingemann, K., Hertzberg, J., Surmann, H.: 6d SLAM - 3D mapping outdoor environments. Journal of Field Robotics 24(8-9), 699–722 (2007)
7. Oksanen, T., Visala, A.: Coverage path planning algorithms for agricultural field machines. Journal of Field Robotics 26(8), 651–668 (2009)
8. Pedersen, S., Fountas, S., Have, H., Blackmore, B.: Agricultural robots - system analysis and economic feasibility. Precision Agriculture 7(4), 295–308 (2006)
9. Slaughter, D., Giles, D., Downey, D.: Autonomous robotic weed control systems: A review. Computers and Electronics in Agriculture 61(1), 63 – 78 (2008)
10. Wellington, C., Campoy, J. abd Khot, L., Ehsani, R.: Orchard tree modeling for advanced sprayer control and automatic tree inventory. In: Proc. IROS Workshop on Agricultural Robotics (2012)