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Abstract
Purpose – The purpose of this paper is to describe a methodology for characterization of the robot environment to help solve such problem as designing an optimal agricultural robot for a specific agricultural task.
Design/methodology/approach – Defining and characterizing a task is a crucial step in the optimization of a task-specific robot. It is especially difficult in the agricultural domain because of the complexity and unstructured nature of the environment. In this research, trees are modeled from orchards and are used as the robot working environment, the geometrical features of an agricultural task are investigated and a method for designing an optimal agricultural robot is developed. Using this method, a simplified characteristic environment, representing the actual environment, is developed and used.
Findings – Case studies showing that the optimal robot, which is designed based on the characteristic environment, is similar to the optimal robot, which is designed based on the actual environment (less than 4 per cent error), is presented, while the optimization run time is significantly shorter (up to 22 times) when using the characteristic environment.
Originality/value – This paper proposes a new concept for solving the robot task-based optimization by the analysis of the task environment and characterizing it by a simpler artificial task environment. The methodology decreases the time of the optimal robot design, allowing to take into account more details in an acceptable time.

Keywords Agriculture, Robot design, Field robotics, Robot task characterization

Paper type Research paper

1. Introduction

Commercial agricultural robots are scarce (Bechar, 2010; Bac *et al.*, 2014). Although industrial robots are frequently universal and could potentially be fitted to many agricultural tasks, their high weight, power consumption and costs make them inappropriate for agricultural use. For these reasons, simpler robots for specific agricultural tasks have been designed (Sakai *et al.*, 2005; Belforte *et al.*, 2006; Scarfe *et al.*, 2009). Additionally, optimal robot task-based design was done for specific tasks (Han *et al.*, 2007; Van Henten *et al.*, 2009). Nevertheless, till now, the optimal design was not based on an accurate environment models, hence, it cannot guarantee that the designed robot is optimally fitted to the task. The goal of this paper is to analyze the robot working environment and creating a characteristic environment, helping to find the optimally fitted robot based on the accurate environment models in an acceptable time. This procedure is defined as a methodology for describing and characterizing of the environment of the robot's task for optimal robot design.

Typically, robot optimization problem is complex to solve numerically. A search for the optimal robot kinematics can take hours or even days of computation time (Bergamaschi *et al.*, 2008; Leger and Bares, 1999). The runtime for the optimization of the agricultural robots is one order of magnitude higher because of the complexity of the environment, consisting of hundreds and thousands of elements. This complexity can be decreased (Han *et al.*, 2007; Van Henten *et al.*, 2009) on account of the amount of information influencing the resultant robot. We propose a novel methodology that analyzes and saves the information needed for the optimal robot design and provides reliable results (compared with the optimal robots achieved by the solution of the whole original optimization problem).

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Generally, the methodology systematically analyzes and simplifies the constraint of a robot optimization problem, allowing a solution of a more complicated problem in less time with acceptable accuracy.

1.1 Simplified example

We consider the common industrial pick-and-place task of randomly oriented objects from a conveyer belt [Figure 1(a)]. A SCARA robot is suitable for this task; nevertheless, the dimensions and the location of the robot have to be found to fulfill this task with minimal efforts. For example, the robot reach has to be sufficient to reach all the objects. Also, to perform the task in acceptable time, the robot has to be sufficiently large, but not too big to reduce energy consumption. The optimal kinematics of the robot performing the task can be found by the optimization of the cost function consisting of all of these aspects. The task and the geometric features of the environment influence the optimal result. The farthest object (along the Y axis) defines the robot reach. The distribution of the location of the objects on the conveyor belt (along the Y axis) defines the locations with a large number of objects, which must be frequently visited by the robot. The distribution of the object orientation (around the Z axis) defines the most frequent orientation of the robot end-effector and the limits of the orientations. To ensure the fulfillment of all these statistical requirements, the robot optimization must be based on the task model consisting of a large number of objects from the actual task. The number of tested objects must be large enough, such that adding more objects to the task model will not influence the result of the optimization.

When the evaluation of the optimization cost function takes a long time (which is typical for the robot optimization), the optimization runtime, based on a large number of objects, can become unacceptable. To decrease the number of objects, the geometric features of the environment can be analyzed, and the whole environment can be characterized by a small number of typical cases. For example, according to the distribution of the object location along the Y axis, presented in Figure 1, the characteristic limits, including 95 per cent of the objects, are depicted by lines, and the most frequent object location is depicted by an asterisk. Then, the entire environment consisting of a large number of objects can be converted into a characteristic environment, including two objects, defining these limits, and one (or a small number) object defining the configuration of the robot, which will be achieved by the robot in most typical cases.

Two motivations of this work are illustrated in the example above. First, we design a robot optimally fitted for a specific task. Second, to find this optimized robot, we use a characteristic set describing the original set.

1.2 Task-based design

One of the main reasons for developing a "task-based robot" is the need to reduce a robot's costs by decreasing its complexity. This task-based robot should be simpler and more effective than a robot that has been optimally fit to carry out a number of tasks.

We split the robotic task into two domains: action and environment. The action includes the motions of the robot, such as approaching a fruit in a fruit picking task. The environment consists of all physical objects influencing the robot's performance, such as robot targets and obstacles, which are located inside the working space. Their geometry, position and orientation (pose) are used as the *constraint* for the optimization of the robot's kinematics. This constraint defines a set of robot poses required to fulfill the task.

The cost effectiveness of the robot can be achieved by the *task-based optimization*, i.e. minimizing of the *cost function*, while fulfilling the *constraint*. The cost function can consist of time, energy, weight, monetary cost, etc., and depends on the customer's demands. The cost function is not influenced by the constraint and is beyond the scope of this research.

Similar agricultural task, such as fruit picking, can differ in different environments. For example, orange, pear and mango trees (Figure 2) have different shapes and dimensions, defining different harvesting tasks and, consequently, different requirements for the robot structure. Most orange fruits grow on the external layer of the tree; thus, the robot can move its end-effector to the fruit location along obstacle-free trajectories. In contrast, pears grow along the branches; thus, in order to reach them, the robot has to penetrate inside the tree canopy and avoid collisions with branches. Lastly, mango fruits grow in the lower part of the tree with a near vertical orientation, thus, unlike the previous cases, the robot could be relatively small and its end-effector orientation could be fixed. These examples of environments demonstrate the constraints of the optimization, which may lead to different optimal robots.

Figure 1 A simple example of a pick-and-place industrial task and distribution of the object location along the Y axis with the most frequent value, depicted by asterisk, and the typical limits, depicted by lines

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Figure 2 Agricultural tasks with obvious structure differences

Note: Orange, pear and mango picking

1.3 Previous works on task-based design in agricultural robotic manipulators

Task-based robotic design in the industrial domain is common and was considered in a number of researches. Wunderlich (1991) designed a robot covering the working volume inside a box modelling the interior of a vehicle. Paredis and Khosla (1996) considered a task in highly restricted space. Leger and Bares (1999) used exact task environment and motions for satellite maintenance. In agriculture, task-based robot design is sometimes used with general guidelines and without optimization. Sakai *et al.* (2005) designed a 2.8-m-reach robot able to hold 15-kg payload that was used for watermelon harvesting. Belforte *et al.* (2006) constructed a robotic arm for greenhouse applications "with standard components and simple home-built parts". Scarfe *et al.* (2009) used a "light, simple and cheap" arm for kiwi harvesting. All these robots are lightweight, with low number of degrees of freedom (DOF), actuated by simple actuators and having other features increasing their simplicity. However, the kinematics of these robots were not systematically fitted to the features of their tasks.

An accurate way to make the task-based design is by conducting a task-based optimization of the agricultural robots. Han *et al.* (2007) designed an optimal robot for eggplant harvesting. The "required rectangular working space" based on the "common plant height, fruit distribution and circumference" was defined as the environment. The robot working space containing this environment was minimized. Van Henten *et al.* (2009) performed robot optimization for cucumber harvesting. The task was constructed based on the "most difficult cases". Although these tasks, which are taken as the constraint for optimization, are based on the features of the actual agricultural tasks, they are not sufficiently effective for robot optimization. A "worst-case" approach leads to a "universal", rather than "optimized", robot. In addition, both an environment modeling and a statistical analysis are required to design a robot which is suitable to its actual task environment.

1.4 Environment as the constraint of the robot optimization

A robot fitted to its actual task environment is able to approach a defined number of targets, avoiding all collisions with the branches, i.e. interact with the environment. This interaction is an optimization constraint, and if it is not fulfilled, the robot is not fitted for the task. The simplest way to define a constraint (environment) is to model *all* the trees in the orchard, describing all possibilities for approaching the fruit while avoiding collisions. Ideally, this would be the most accurate way to define the constraint to design the optimal robot; yet, it is impractical to measure and model an entire orchard. Thus, statistical sampling must be performed to achieve a sample data that characterizes the environment. If the sampling data are too big, it causes a combinatorial explosion while solving the optimization problem (especially in manipulator trajectory planning and target sequencing) which increases the optimization runtime, one of the main limitations in the robot design process. Therefore, a simple environment model including a small amount of data representing the actual environment is effective for robot optimization.

1.5 Optimization runtime

The optimization runtime is a concern in many studies (reviewed by Bergamaschi *et al.*, 2008). Typically, in such cases, the number of optimization parameters is large, and while taking into account the complexity of the cost function, it leads to a long optimization runtime. One of the methods to decrease this runtime is to define an appropriate optimization algorithm. Bergamaschi *et al.* (2008) and Shiakolas *et al.* (2002) investigated different algorithms and pointed the most effective ones for robot optimization. To the best of our knowledge, environment characterization as a method to decrease the optimization runtime has not been found in previous works and is the focus of this research.

1.6 Environment modelling

Environment modelling is a basic step in the environment characterization. Several research studies conducted environment analysis using accurate agricultural environment models. Edan *et al.* (1991) measured location of orange fruit to achieve an efficient trajectory for a specific robot. Lee and Rosa (2006) measured location of orange fruits to develop a fruit picking technique.

There are three common used methods for plant reconstruction and modeling:

1 based on visual images (Santos and Ueda, 2013);
2 3D scanning (Preuksakarn *et al.*, 2010; Méndez *et al.*, 2014; Cheein *et al.*, 2015); and
3 a mechanical sampling (passive robot devise used by Edan *et al.*, 1991).

2. Materials and methods

2.1 Research assumptions

We have simplified the environment and the robot optimization problem to focus on developing the methodology and to show proof of concept:

1 Robot obstacles (e.g. branches) are not taken into consideration.
2 The robotic arm base is located at a single location. However, finding this optimal location is part of the optimization process.
3 Small changes in the robot work space (e.g. changes in the location of the end-effector) cause small changes in the robot joint space. In general, this is true for all nonsingular robot configurations.

2.2 Environment modeling

The environment of a robot in an agricultural task consists mainly of plants, e.g. trees in an orchard, plants in a greenhouse or open field, etc. In this work, the following features are modeled: branch length, location, orientation and thickness; fruit location, orientation and size; trellis wires; and the ground plane.

To measure and model the features above, we developed a mechanical measuring device, a "digitizer" shown in Figure 3. This digitizer is a passive robotic arm and has a kinematic structure of an RRRR robot (four revolute joints) with three links at lengths of 1.2, 1.2 and 0.4 m. The angles of the structure joints are measured by encoders with a resolution of 0.07°, which results in a total maximum error of 3.5 mm. The location of the tip of the device is calculated according to the forward kinematics of the robot.

In a tree model, the branches are divided into straight intervals and are represented by cylinders. The fruit are represented by ellipsoids with orientation. The ground is modeled as a horizontal plane. Full measurement of a cultivated apple tree takes approximately 3 h using this device.

Figure 3 Digitizer, a mechanical measuring device, is a passive robotic arm with RRRR structure

As a case study of environments characterization, we used an apple and nectarine picking tasks in orchards (Figure 4). The following trees were modeled:

- apple tree trained by the Tall Spindle method referenced as Tree 1 [Figure 4(a)];
- apple tree trained by the Central Leader method referenced as Tree 2 [Figure 4(b) and (c)];
- nectarine tree trained by the vase method referenced as Tree 3 [Figure 4(d) and (e)]; and
- a group of five apple trees trained by the Central Leader method planted successively in a row referenced as Tree Group 4 [Figure 4(b)].

The coordinate system of the plant environment is defined as follows: Y-axis is the tree row line, Z-axis is upwards perpendicular to the ground, and X-axis complements to right-hand system [Figure 4(b) and (c)]. The origin of the coordinate system is at the point that the plant trunk intersects the ground.

According to Assumption 1, the environment is obstacles free in this work. The only objects of interest are fruit; hence, they are considered as the environment objects.

2.3 Robot optimization

A simple optimization of the kinematics of robots for the fruit picking based on the characteristic environment was used as a proof-of-concept for the characteristic environment methodology. We predefine the robots as a four-DOF revolute joint robot (i.e. RRRR) located in a single location along the X-axis. The RRRR robot structure was chosen as the worst case of the nonlinearity of the robot forward and inverse kinematics, representing the mapping between the robot work space and robot joint space. The optimization variables are the parameters defining the robot kinematics and location: the four link lengths L_1, L_2, L_3, L_4, where L_1 is the robot base height, and the distance D_x between the robot base and the tree trunk. The cost function F is constructed according to the designer requirements. In this case, we chose the cost function to be the mean of torques at the robot actuators at the moment of the fruit picking. The torque of the actuators can be used as an index for the actuator power, which defines a significant part of the robot's cost. The torques in the robot joints hold the external forces applied on the robot by the weight of the robot links and the load.

To comply with the fruit picking task, the optimal robot needs to exceed the predefined success rate of the fruit picking, α_{picked}. In this work, we defined α_{picked} to be 95 per cent of the fruit.

Because the main objective of this paper is the illustration of the methodology, we use a simplified robot optimization problem. The complexity of the optimization problem will be left to the designer and may include: the number of the optimization parameters, simulation of the robotic dynamics and motion planning algorithms, simulation of the end-effector, amount of data, etc. The methodology of the environment characterization aids to solve an optimization problem of any complexity in a more effective way.

An optimal robot based on a characteristic environment (RCE) is compared with the optimal robot based on an actual

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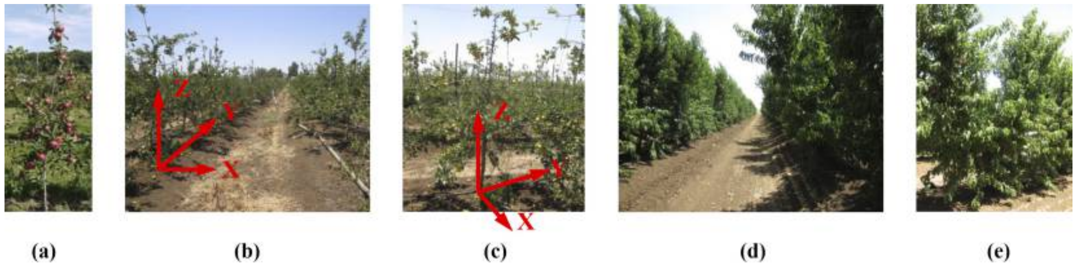
Figure 4 Views of agricultural environments



Note: The coordinate system is shown in (b) and (c)

environment (RAE). The similarity between the robots is evaluated by the relative kinematics difference defined as:

$$dK = \frac{|norm(\overline{K_{RAE}}) - norm(\overline{K_{RCE}})|}{norm(\overline{K_{RAE}})}, \tag{1}$$

where $\overline{K} = (L_1\ L_2\ L_3\ L_4\ D_x)$; and relative cost function differences are defined as:

$$dF = \frac{|F_{RAE\_AE} - F_{RCE\_AE}|}{F_{RAE\_AE}}, \tag{2}$$

where F_{RAE_AE} is the cost function of a robot based on the AE working on the actual environment (AE), and F_{RCE_AE} is the cost function of a robot based on the CE working on the actual environment.

Because the focus of this work is not on the optimization algorithm, we used the brute-force grid search method with a grid of 20 intervals. The advantages of this method are simplicity and testing all the possibilities within the needed resolution.

2.4 Characteristic environment

Characterization of an actual environment is the most important part of the methodology, responsible for finding and keeping the information influencing the optimization result. The characteristic environment is the robot work environment representing the actual environment in the optimization process. It is constructed based on the features of the actual environment. On the one hand, the characteristic environment must include the needed information affecting the optimization solution. On the other hand, it must be the simplest to decrease the optimization runtime. The main *guidelines* for defining such a characteristic environment are as follows:

- Use typical cases, avoiding worst or untypical cases which tend to lead to the design of a universal robot, not an optimal one.
- Use the minimal amount of necessary information defining the environment.

For this purpose, we developed the environment characterization method using characteristic fruit and cluster probability.

In an actual environment, the distribution of the fruit in the space is not uniform. The fruit are concentrated in clusters representing areas with high fruit density, for example, fruit growing on a branch. If the cluster is small enough, and all fruit on it are located close together, according to Assumption 3, the robot configurations for picking these fruit are also close (in the robot configuration space). Therefore, all the robot configurations for picking the fruit from this cluster can be characterized by a configuration typical to this cluster. The cost function values of picking these fruit are also close and can be represented by the cost function value of the characteristic robot configuration. Nevertheless, as the robot still has to be designed, the robot configuration space cannot be used, and only characterization in the work space can be made.

The fruit, which can be picked by the assumed characterizing robot configuration, is the *characteristic fruit* representing the fruit cluster in the robot work space. Because this fruit is intended to characterize the location of the cluster, its location is taken in the geometric center of the cluster, and this characteristic fruit is called the *mean characteristic fruit*.

The computation of the cost function for picking all fruit in the cluster is replaced by the computation of the cost function for the mean characteristic fruit. However, clusters containing different number of fruit have different influence on the total cost function. The more fruit are in a cluster, the more frequently the robot end-effector has to visit this cluster, and to be fitted to work in this cluster. Thus, the clusters are characterized also by the fruit number (which is divided by the total fruit number for normalization purpose). This characteristic is called *cluster probability* P_i (probability of the robot to visit cluster i).

In this work, the cost function F for picking all the fruit in a tree is the average of the cost function values for picking each fruit separately F_i (see Section 2.2). Its actual value, F_{act}, is calculated by:

$$F_{act} = \frac{\sum_{i=1}^{N_{act\_fruit}} F_{i,act}}{N_{act\_fruit}}, \tag{3}$$

where N_{act_fruit} is the number of actual fruit on the tree, and $F_{i,act}$ is the cost function for picking the i's actual fruit. This cost function can be evaluated by the mathematical expectation F_{char}, which is calculated knowing the probability of the characterized fruit clusters:

$$F_{char} = \sum_{i=1}^{Ncfruit} F_{i,char} P_i, \tag{4}$$

where N_{cfruit} is the number of characteristic fruit, and $F_{i,char}$ is the cost function for picking the *i*'s characteristic fruit.

However, while providing good evaluation of the cost function, the mean characteristic fruit can fail in characterizing the robot working volume dimensions. The simplification of the characteristic environment, which is one of the goals of the characterization, can be achieved by decreasing the number of the characteristic fruit caused by the increasing the cluster size. But for some small number of the characteristic fruit, the clusters size might become too big. Then, while approaching the characteristic fruit in the center of the cluster, the robot might not be able to reach the extreme fruit of the cluster, which is needed to fulfill the optimization constraint.

To solve this problem and characterize the maximal robot reach, the *extreme characteristic fruit* is used. If the robot base location is known, the extreme characteristic fruit is the fruit farthest from the robot base location. But, as the robot base location is being searched during the optimization, and, consequently, is unknown during the environment characterization, extreme characteristic fruit cannot be found, but has to be evaluated based on the robot work space. The distance of the robot base from the tree trunk (D_x) is assumed to be equal to the maximal fruit X coordinate X_{max} shifted by 0.3 m (assumed minimal distance between the robot base and end-effector), $D_x = X_{max} + 0.3$. The height of the robot base (L_1) is defined as half of the tree height. If an assumption about a single robot base location is insufficient to characterize the extreme fruit, assumption about two or more locations can be made.

To fulfill the guidelines and to avoid worst cases, the extreme fruit must be taken not as the fruit which are farthest from the robot base. Because the robot has to approach no less than α_{picked} = 95 per cent of the fruit, it may not need to approach the rest 5 per cent of the fruit causing the highest values of the cost function. According to the definition of the cost function, its highest value corresponds to the largest robot reach. Then the extreme fruit must be the farthest fruit among the 95 per cent of the nearest fruit.

Thus, according to the definition of the mean and extreme characteristic fruits, the mean characteristic fruit are responsible for the minimization of the cost function, while the extreme characteristic fruit is responsible for satisfying the optimization constraint.

2.4.1 Building the characteristic environment

Characteristic environment can be constructed in different ways. In this paper, we propose a method fitted to the guidelines described in the introduction, according to which the characteristic environment consists of two types of the characteristic targets: mean and extreme characteristic targets.

The distribution of the fruit over the clusters is calculated by the K-mean algorithm (Press *et al.*, 2007) over the 95 per cent of the nearest fruit. The cluster size must be small enough to comply with Assumption 3. Therefore, the number of clusters is found such that the size of all the clusters is less than a specific size (or is bounded by a sphere with some radius).

The characteristic environment can be built for a single tree and for a group of trees. The fruit of the trees composing the group are merged and are considered as a single tree.

3. Results and discussion

3.1 Environment modeling

Apple and nectarine tree models (described in Section 2.1) were built using the measuring device (digitizer). The models, presented in Figure 5, include branches, fruit and trellis wires. Fruit are shown as red dots in the second and third rows in Figure 5. The models of the Tree Group 4 are presented in Figure 6.

3.2 Characteristic environment

The characteristic environment (CE) is constructed based on the actual environment (AE) and consists of the mean and extreme characteristic fruit. Examples of characteristic environments are presented in Figure 7. To illustrate the characterization, the fruit of the AE are presented on the same plot with the characteristic fruit of the CE.

The assumed locations of the robot base are represented by squares. Further, 95 per cent of the actual fruit nearest to the assumed robot base are divided into the clusters shown by different colors. The number of the clusters for each CE is defined by the maximal cluster size. The smaller is the cluster size, the more detailed is the characterization of the AE, but the more complex becomes the CE. By trial and error, we have found that the cluster bounded by a sphere with radius five times less than the radius of the sphere bounding the tree is successful for the characterization. The number of the actual fruit and the number of the clusters (number of fruit of the CE) are shown in Table I.

The mean characteristic fruit of each cluster are shown as asterisks, with the numbers representing the cluster probability. The extreme fruit are marked by circles; 5 per cent of the farthest fruit are colored in black. The fruit unpicked by the robot based on the AE are marked by the triangles.

The characteristic environment for Tree Group 4 is presented in Figure 8. The number of clusters and the number of fruit are shown in Table III. To characterize the extreme fruit, unpicked by the optimal robot, we use two assumed locations for the robot base (in Figure 8 two squares at 1/3 and 2/3 of the average tree height) and two extreme characteristic fruit (two circles).

3.3 Robot optimization

The optimal fruit-picking robots based on an AE are compared with the optimal robots based on a CE. In Table I, we present the optimization results including the optimal robots kinematics, the cost function, relative differences and computation time.

N_{fruit} shows the number of actual fruit in the AE and the number of characteristic fruit in CE. The ratio between the N_{fruit} for the AE and the CE defines how much the CE is simpler than the AE, which influences the optimization runtime factor k_t, defined as the ratio between the runtime for optimization based on AE and the runtime for optimization based on CE.

The kinematics and the location (L_1, L_2, L_3, L_4 and D_x) of the optimal robots are similar for the robots based on the AE and robots based on the CE. The relative difference, *dK*, is less than 12 per cent for the worst case and 8.6 per cent on average. The robot cost function, *F*, is also similar. The relative difference, *dF*, is less than 6.2 per cent (4 per cent on average). The low differences between the robots based on the AE and robots based on the CE show that the robots based on

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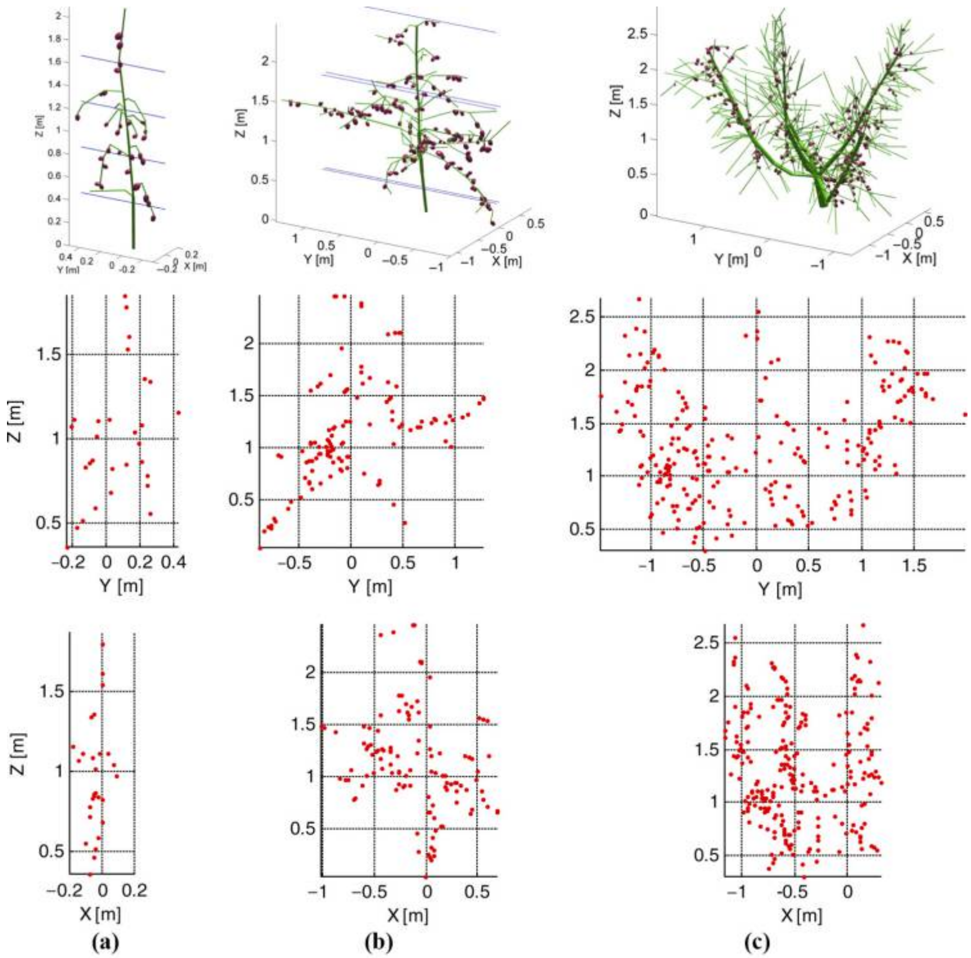
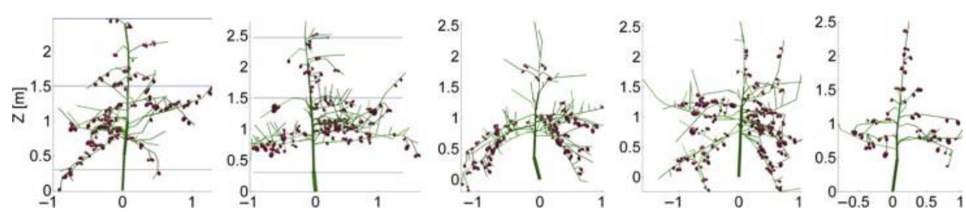
Figure 5 An isometric view of the modeled tree and the frontal and the side views of the fruit on the trees (the first, second and the third rows respectively)



Notes: The modeled trees are (a) apple Tall Spindle, (b) apple Central Leader, and (c) nectarine

Figure 6 Frontal view of the Central Leader apple tree models composing Tree Group 4



the CE can represent the robots based on the AE with runtime shorter up to 22 times (15 times on average).

The number of picked fruit, α_{picked}, is similar for the robots based on the AE and the CE, meaning that that robots based on the CE are adequate for the fruit picking task (or close for Tree 3), but, at the same time, they are not planned to deal with the worst cases of the fruit locations, and therefore, are shorter and simpler than they could have been in the case of picking 100 per cent of the fruit.

The optimal fruit picking robot for Tree 2 is presented in Figure 9. All robot configurations for picking the actual fruit of the AE [Figure 9(a)] and the characteristic fruit of the CE [Figure 9(b)] are presented. The unreachable fruit of the AE are colored in black.

Optimal robot designed for the AE including a group of trees is compared to the robot based on the CE in Table II and Table III. The optimal robot has to pick more than α_{picked} fruit for the entire group. The relative difference between the robot based on the AE and the robot based on the CE in kinematics and location is $dK = 12$ per cent. Nevertheless, the weighted cost function F_{tot} is similar for the both robots, $dF = 0.3$ per cent. Most importantly, the optimization runtime for the robot based on the CE is 38 times shorter than the runtime for the robot based on the AE optimization.

Figure 7 Isometric, frontal, and side views of the characteristic environments for (a) Tree 1, (b) Tree 2 and (c) Tree 3 with the actual fruit on the same plot

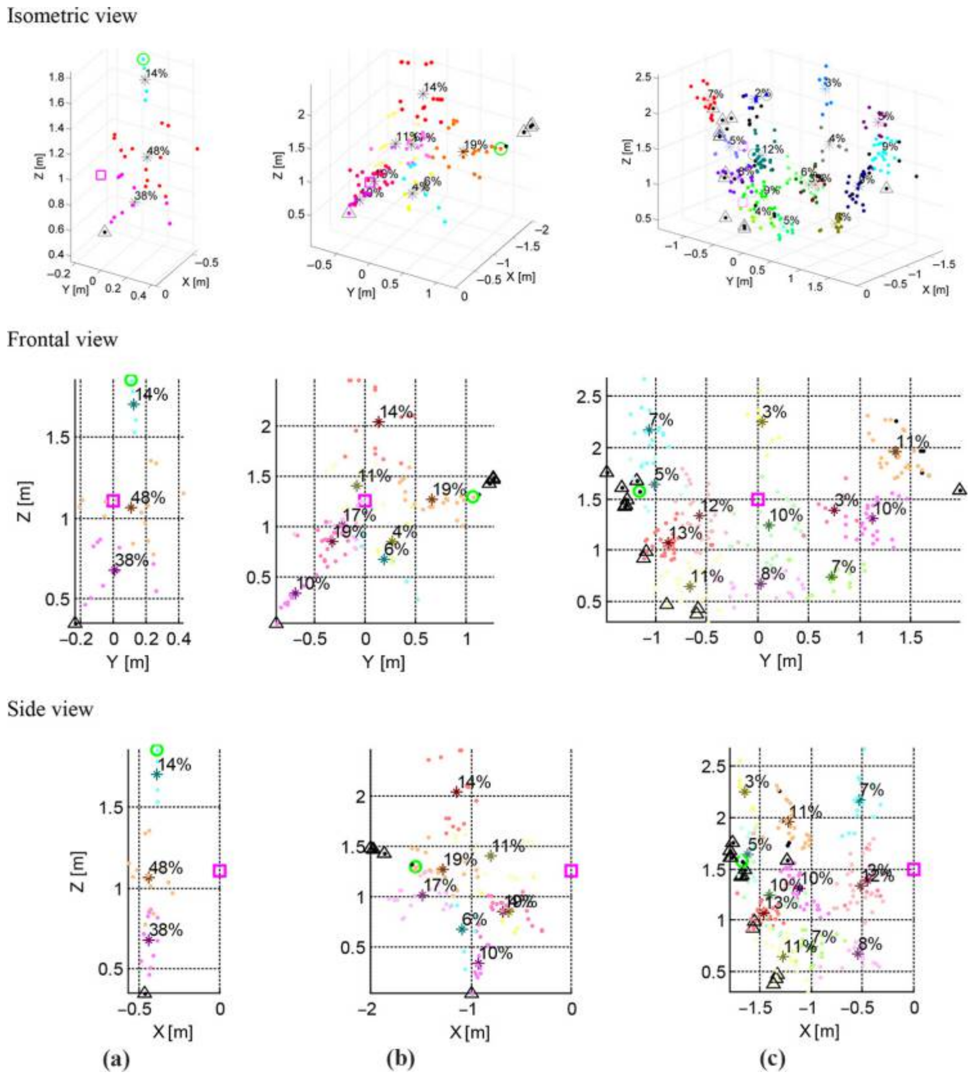


Table I Comparison of the optimal robots designed based on the AE and CE for single trees

Robot type	N_{fruit}	L_1	L_2	L_3	L_4	D_x	F	α_{picked} (%)	dK (%)	dF (%)	k_t
RAE Tree 1	30	1.52	0.70	0.50	0.10	0.39	20.25	96.7	4	3.5	4.7
RCE Tree 1	6	1.45	0.70	0.50	0.10	0.39	20.97	100			
RAE Tree 2	144	1.65	1.28	0.61	0.10	0.99	45.14	95.1	12	2.3	18.5
RCE Tree 2	10	1.65	1.07	0.76	0.10	0.99	46.20	96.1			
RAE Tree 3	261	1.89	1.33	0.66	0.10	0.62	52.84	95.4	10	6.2	22
RCE Tree 3	14	2.09	1.44	0.61	0.10	0.62	49.54	90.8			

The cost function value and the percentage of the picked fruit are detailed for each tree in the group in Table III. The cost function F and the percentage of the picked fruit α_{picked} values are similar for all trees, meaning that the robot based on the CE is satisfactory and not redundant for this task.

4. Conclusion

In this paper, a new methodology for improving the design of an agricultural robotic arm is proposed. Using statistical analysis, this methodology generates a characteristic environment, providing reliable characterization of an agricultural environment. The characteristic environment, which gives a good approximation of the solution based on the actual environment. According to the given examples, the difference in the cost function of the optimal robot based on an actual environment and optimal robot based on a characteristic environment is less than 6.2 per cent, while optimization time for the characteristic environment is up to 22 times shorter for a single tree.

Figure 8 (a) Frontal, (b) side and (c) isometric views of the characteristic environment for Tree Group 4 with the actual fruit on the same plot

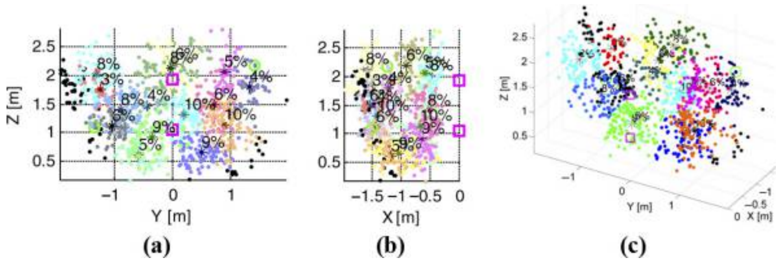
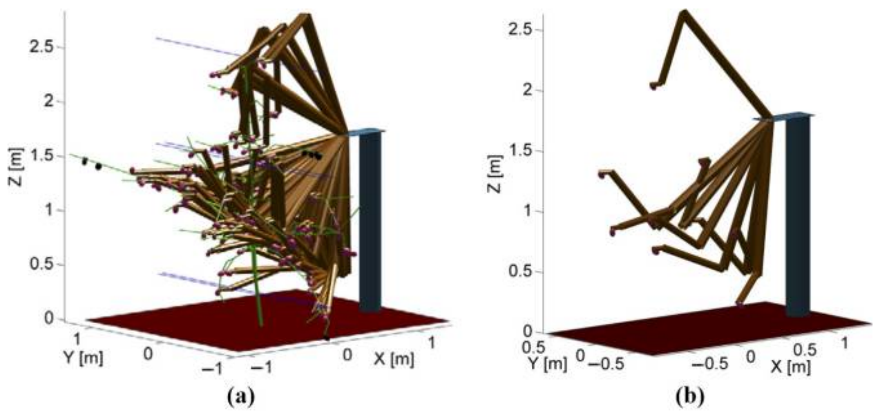


Figure 9 Robot with optimal kinematics and location picking fruit at the Tree 2



Notes: The robot configurations are presented at the moments of the fruit picking for (a) the actual fruit of the AE and (b) the characteristic fruit of the CE

Table II Comparison of the optimal robots designed based on the AE (RAE) and CE (RCE) for Tree Group 4

Robot type	N_{fruit}	L_1	L_2	L_3	L_4	α_{picked}	F_{tot}	dK (%)	dF (%)	k_t
RAE Tree group 4	725	1.58	1.49	0.92	0.10	95.2	63.6	12	0.3	38
RCE Tree 4	17	1.40	1.33	1.03	0.10	94.6	63.5			

Table III Comparison of the optimal robots designed based on the AE (RAE) and CE (RCE) for each tree in the Tree Group 4

Tree no.	N_{fruit}	D_x RAE	D_x RCE	F RAE	F RCE	dF (%)	α_{picked} RAE (%)	α_{picked} RCE (%)
1	*144*	*0.98*	*0.98*	*59.20*	60.19	1.7	97.9	100
2	164	1.68	1.68	71.20	71.04	0.2	96.9	96.9
3	136	1.30	1.30	59.92	60.89	1.6	91.9	91.9
4	216	1.35	1.35	63.97	62.39	2.4	92.6	89.8
5	65	1.17	1.17	60.84	60.89	0.0	100	100

The time-saving advantage of this method becomes significant in the design of a robot based on environments consisting of a number of trees, in our case, by 38 times for the environment consisting of five trees. The number of trees characterizing an actual orchard can be much larger, and the optimization time could be decreased by two to three orders of magnitude. This methodology will be used as the basis for more realistic robot design, including obstacle avoidance (branches and trellises), multiple robot locations around the tree, different robot topologies and DOF, etc. In this case, the decreasing of the optimization run time, which can take more than a week, is critical.

The specification of the geometric structure of the task's environment, such as typical boundaries of the environment (extreme characteristic fruit) and the typical areas visited by the robot's end-effector (mean characteristic fruit), becomes clear during the construction of the characteristic environment. Knowing these features, a designer can make assumptions about the robot's structure, for example, defining the number of DOF or the robot's reach. These assumptions can simplify the optimization process, and allow evaluating the applicability of a robot optimal for one specific task to other tasks.

Environment characterization provides information about the simplest and worst cases for the robot operation. This information can be used to solve such problems as design of the agricultural environment fitted to the operation by robots.

The environment characterization methodology quickens the optimization process of designing an optimal robot for a specific agricultural task. It can also be applied to any robotics area where a task-based robot must be designed, and the environment is complex or unstructured.

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