Flower pollination using point-cloud measurements and POMDP

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I. Extended Abstract

Pollinators are responsible for the reproduction of many plants by transferring pollen from one flower to another. This "free service" provided by nature is vital for fruit and seed production, which are the basis for human agriculture. Nevertheless, over the last decades, the population of natural pollinators has experienced a big decline caused by several reasons, as exposure to pesticides, loss of habitat, the spread of diseases, and climate change [1].

Although the survival of the natural pollinators is essential, and their loss would lead to extreme economic impact and other important externalities [2], precision robotic systems can help to execute the pollination tasks in a cost-effective and stable form. Most of the methods explored so far do not make the robot interact with a flower as a bee would, by touch. One exception is the Bramblebee robot that consists of a robotic arm mounted on top of a mobile base and that touches the flowers using its end-effector [3].

One of the challenges of designing a robot that interacts with a flower is to achieve a good estimate of the flower pose before proceeding with the pollination procedure. In their previous work, this estimate was achieved by executing a predefined sequence of actions with the robotic arm [4]. However, this process can be performed with a higher degree of autonomy using reinforcement learning. Considering that the flower localization problem is subject to a lot of uncertainty caused by factors like sensor noise, sensor resolution, flower unknown geometry, and flower detection and segmentation, one possible solution framework is to use partially observable Markov decision processes (POMDPs) to allow for principled decision making under conditions of uncertain sensing [5].

The goal of this work is to generate a policy that will make the arm pollinate the flower under the uncertainty of the sensor measurements. The sensor provided is a stereo camera, which is capable of generating a point cloud of the environment containing background and the flower as depicted in Fig. 1.

The approach will be divided into three parts. The first part consists of generating a simulation framework that uses a stereo camera to get point cloud data from flower models. This point cloud will be segmented to extract a single flower and segmented clouds will be recorded for a range of possible configurations of the flower with respect to the camera frame. The second part consists of creating the observation model given by $h(x_t)$ and $R_t(x_t)$ for the POMDP solver. The measurement function $h(x_t)$ will be created using the center of mass of the point cloud to obtain the position of the flower and using Principal Component Analysis (PCA) to extract a normal vector of the point cloud and, consequently, its orientation, assuming it looks like a disk. The noise function $R_t(x_t)$ is expected to be also dependent on the states because seeing the flower from more oblique orientations will assume the flower disk model fails. To get this function we want to use the true pose and check the deviation from the estimated values.

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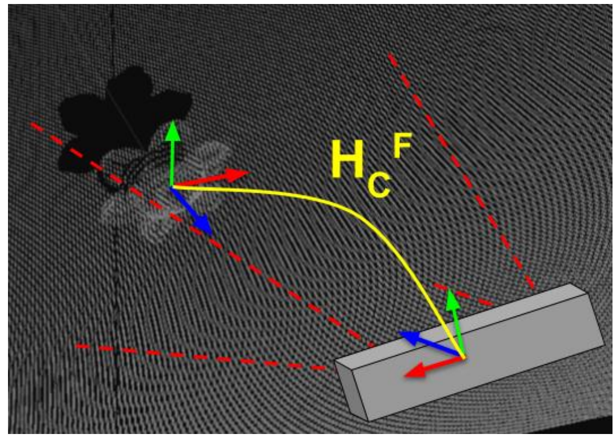

Fig. 1. Flower pose estimation. The goal is to obtain the homogeneous transformation matrix H_C^F from the camera frame C to the flower frame F.

$$\begin{aligned} \min_{u,\mu,\Sigma} \quad & \sum_{t=0}^{H} c(\mu_t, \Sigma_t, u_t) \\ \text{s.t.} \quad & x_{t+1} = f(x_t, u_t) \\ & z_t = h(x_t) \end{aligned} \tag{1}$$

The third part consists of solving the POMDP problem, shown in 1, and obtaining a policy that takes as inputs the belief state of the flower (μ_t, Σ_t) and outputs the best action, by minimizing the cost function $c(\mu_t, \Sigma_t, u_t)$, which will take into account reward successful pollination actions, penalize actions moving the arm to reduce uncertainty, and strongly penalize unsuccessful pollination actions. The POMDP problem will be solved using the offline approximated solution method SARSOP [6], which takes as inputs all possible state combinations that we expect to encounter and outputs best actions for each of them. This policy is the expected outcome of this work.

References

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