Inspection of Large-Scale Solar Plants by an Autonomous Drone: Planning and Control

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***Abstract*—Solar power plants are large-scale infrastructures that require regular inspection operations, to verify that each panel is functioning as desired. Thermal imaging is often used since variations in the panel temperature can be used to recognize a possible failure. Drones can be applied, being ideally suited for monitoring large areas in a short time: a drone equipped with an infrared camera is thus flown over each panel. Visual data from a standard camera can also be integrated into the analysis. However, these operations can still be time-consuming for larger plants; moreover, a skilled operator is needed during the entire inspection, and it is not obvious how to optimize the route over the whole set of panels (also taking into account battery constraints). A semi- or fully-automated system is thus of practical interest. Here, we present our current work (in collaboration with a company that performs such inspections), proposing an automated drone system for solar plants. First, a satellite picture is automatically downloaded (knowing the coordinates of the plant); this image is analyzed by a state-of-the-art machine learning algorithm that detects the positions of the panel lines. Then, the software finds the optimal route passing over each panel, by solving a Travelling Salesman Problem. This route is followed by the drone over the plant, employing a visual servoing algorithm. We have gathered preliminary results from both simulations and tests in our laboratory: we successfully demonstrated both the route planning phase and the visual servoing algorithm.**

***Index Terms*—unmanned aerial vehicles, photovoltaic plants, visual servoing, machine learning, route planning**

I. Introduction

In the last decades, drones[1] have seen explosive growth in capabilities and ease of access. They have thus attracted a strong research interest, from academic groups, industries, and militaries, and have found usage in many tasks, including load transport, surveillance, and reconnaissance. We are interested in drones for monitoring, for instance, of port infrastructures (such as docks), pipelines, crops in fields, and in search-and-rescue operations [1]. Towards these goals, most drone designs include vision systems that provide the user with a real-time video feed, which is also helpful for guiding the drone.

An application where drones are already routinely used is the inspection of solar power plants, which generally employ arrays of photovoltaic (PV) panels to produce energy: these panels are prone to surface defects, which can be easily diagnosed by visual elements (such as local discolorations or cracks) or by surface temperature changes [2, 3]. One then needs detailed pictures taken over large areas, also using thermal cameras. Drones can freely fly above the panels and thus reduce inspection time and cost. Notably, PV panels are always directly visible from above; also, drones in this case do not fly over people, which assuages safety concerns. This application is of ever-increasing interest as the push for renewable energy becomes stronger and more PV plants are built.

In current practice, as confirmed by industrial partners, the drone is controlled either manually or by passing over preselected waypoints [4]. This approach, however, has disadvantages: first, it does not allow for autonomous flight, which would relieve the operator from the need to always supervise the drone. This research directive is of growing relevance as air authorities are moving towards regulating fully autonomous flight, which is currently not allowed by international standards. Another limit is that planning a route that fully covers every panel is both tedious and not trivial; the optimization of said route, to minimize the flight time, is a complex problem, especially when battery constraints are considered.

II. Panel Recognition

In our work, we consider an inspection system that does not require human intervention (except for supervision and safety). The work is currently under development in partnership with JP Droni, a local company that routinely performs inspections with drones as a service for PV plant operators.

The general concept of the aerial inspection system is illustrated in Fig. 1. The first step of the procedure is to analyze satellite images, using a software tool we developed in which the user highlights the areas of interest where the panels are placed; in a future development, this procedure could also be automated using known approaches [5]. The panels are then selected from the image by a *Neural Network* (NN), which was trained on a custom-made data set (Fig. 2a); we used the project *PointRend* within the *Detectron2* library (developed by Meta), as it is an established tool for semantic segmentation, but other similar frameworks could also be applied [6]. The *OpenCV* library was used to convert the generic-shaped masks thus obtained into rectangles. Two waypoints are defined for each panel (in the middle of the shorter sides): the drone must visit both in succession, to ensure that it passes over the panel.

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[1]Acronyms such as UAVs (*Unmanned Aerial Vehicles*) are also used, although less often, with an essentially equivalent meaning.

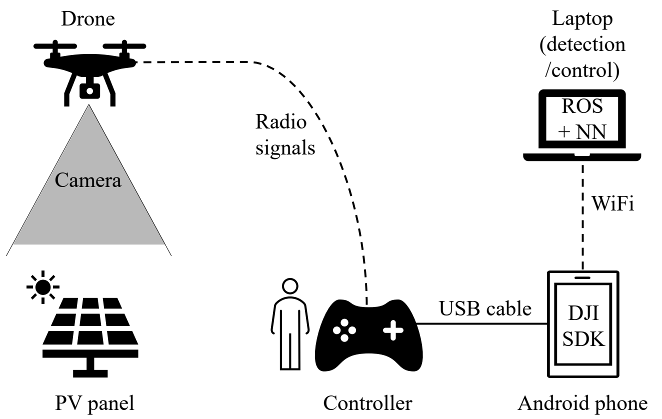

Figure 1. Schematic of our system. An Android application (on a mobile phone) acts as a "bridge" from the detection software to the remote controller; the drone receives the control signals and sends the visual feed to be analyzed.

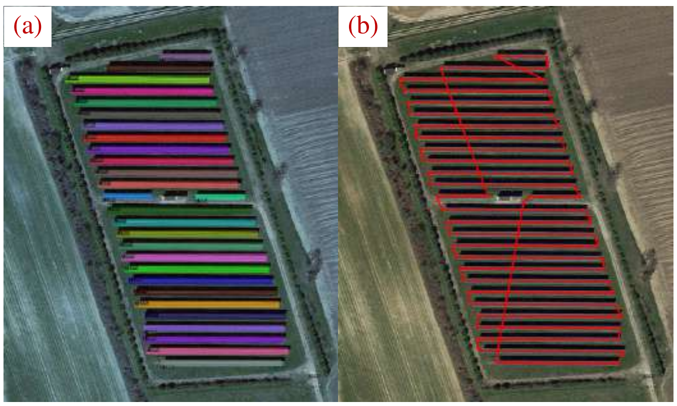

Figure 2. Left: satellite image, with the panels labelled for training the detection algorithm. Right: the optimal route, passing over each panel.

III. Route Planning

Finding an optimal route through the waypoints (Fig. 2b) is a special instance of the *Travelling Salesman Problem* (TSP), for which many approaches are known. The optimal route has to pass through required edges (one for each panel) and the drone has to return to the take-off point before the battery is depleted[2]. We used simulated annealing optimization, from a dedicated Python library, and a branch-and-cut solution where we implemented a modified TSP instance in the state-of-the-art software IBM CPLEX; the battery constraint was tackled by grouping the panels using the *k-means* algorithm. CPLEX finds a route that is guaranteed to be optimal, which we can then compare with the solution from our heuristic method.

IV. Visual Servoing

With the route completely defined, the drone position could be controlled by simply using GNSS data from onboard sensors. However, this approach can be improved by using the real-time video feed to move the drone; in other terms, a *visual servoing* system detects the position of the panel underneath the drone and adjusts the velocity accordingly. This increases the accuracy of the motion and the robustness against noise; moreover, it allows the drone to fly at lower heights, obtaining more detailed images for inspection [4]. A ROS controller was developed that receives images from the drone camera, analyzes them with a second NN trained on a custom data set, and computes control signals. In our tests, we applied three concepts, namely a PID controller, a Lyapunov (non-linear) one, and a visual-servoing- and task-stacking-based controller.

[2]The recharge time is neglected, as the battery can be quickly replaced.

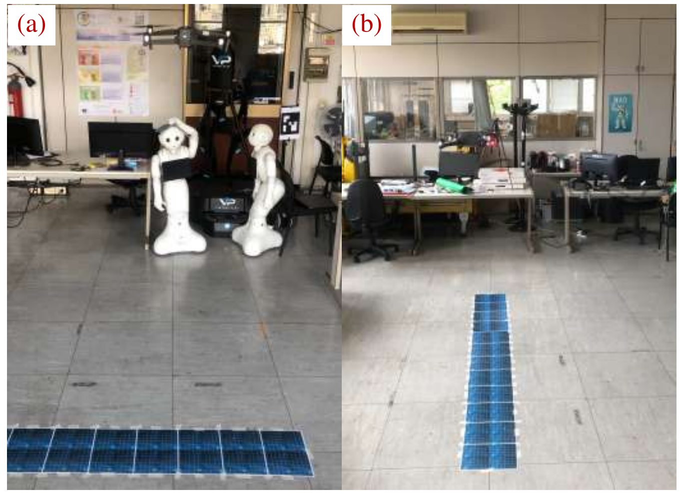

Figure 3. Example of a test: the drone flies over a row of printed PV panels.

V. Simulations and Experiments

Tests are currently being carried out in our laboratory with a DJI Mavic 2 Enterprise drone; an Android application developed with the SDK by DJI connects the ROS system to the radio controller. We placed printed images of real panels on the ground: it was verified that the drone followed the panel row accurately and uniformly, even in a GNSS-denied indoor environment (see Fig. 3 and the multimedia attachment).

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