3D Map Reconstruction of an Orchard
using an Angle-Aware Covering Control
Strategy

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Abstract: In the last years, unmanned aerial vehicles are becoming a reality in the context
of precision agriculture, mainly for monitoring, patrolling and remote sensing tasks, but also
for 3D map reconstruction. In this paper, we present an innovative approach where a fleet of
unmanned aerial vehicles is exploited to perform remote sensing tasks over an apple orchard
for reconstructing a 3D map of the field, formulating the covering control problem to combine
the position of a monitoring target and the viewing angle. Moreover, the objective function
of the controller is defined by an importance index, which has been computed from a multi-
spectral map of the field, obtained by a preliminary flight, using a semantic interpretation scheme
based on a convolutional neural network. This objective function is then updated according to
the history of the past coverage states, thus allowing the drones to take situation-adaptive
actions. The effectiveness of the proposed covering control strategy has been validated through
simulations on a Robot Operating System.

Keywords: Precision farming, Agricultural robotics, Autonomous vehicles in agriculture,
Covering control, Crop modeling.

1. INTRODUCTION

In modern agriculture, the relevance of the role of Un-
manned Aerial Vehicles (UAVs), also known as drones, is
rapidly growing (Mammarella et al. (2021)). Thanks to
their enhanced capability to perform in-field operations in
a precise and autonomous way, this typology of vehicles
is leading to improvements in the context of the Agricultu-
re 4.0 framework (Radoglou-Grammatikis et al. (2020)
Mammarella et al. (2020)). As detailed in Comba et al.
(2019a), UAVs could allow to extend, both in terms of
spatial and temporal dimensions, the capability to monitor
the crop status during the whole growing season, thanks to light and transportable sensors. Within this
context, UAVs are exploited, for examples, to reveal crop
water stresses (Guidoni et al. (2019)), soil erosion (Lima
et al. (2021)), fungal and pest infestations (Calou et al.
(2020)), etc. Recently, the potential of 3D crop model
informative content for agricultural applications has been
investigated in Comba et al. (2019b), as an alternative
to widely-exploited 2D maps (Primicerio et al. (2015)).
3D map reconstruction through techniques like Structure-
from-Motion (SfM) represents a powerful tool, even if it
still represents a challenging task, due to the fact that the
crop fields usually have poor and/or repetitive textures.
Preliminary promising results have been achieved in the
vineyard context where, thanks to a semantic interpreta-

This work was partially funded by the Italian IIT and MIUR
within the 2017 PRIN (N. 2017JS559BB) and by the Japan Society
for the Promotion of Science (JSPS) KAKENHI under Grant N.
21K04104.
Classical covering control techniques typically requires drones to patrol over the environment by raising or lowering a density function (see e.g. Sugimoto et al. (2015)), according to the history of the past coverage states. On the other hand, to define and apply an effective covering control strategy to the selected field, it is crucial to identify which areas are of higher relevance, e.g. crop canopy, and needs to be detected from various viewing angles to improve the quality of the resulting map. This information can be resumed into a priority map, describing the distribution of the importance index function over the field. Approaches similar to the one presented in Comba et al. (2021) can be exploited to automatically retrieve the 3D-points density function distribution according to the field characteristics, starting from multi-spectral maps.

The main drawback of available covering control strategies is the lack of situation-adaptive features, that does not properly adapt the control action to the relevance and observation rate of each region. This is due because the importance index is defined as a monotonically decreasing observation rate of each region. This is due because the density function, demonstrating the capability of achieving the forward invariance of $C$, i.e.

$$u^*(x) \equiv \arg \min_{u \in U} \|u - u_{nom}\|$$

s.t. (2).

2.2 Problem settings

The selected scenario involves $N$ UAVs, locally controlled such that they are characterized by common and constant altitude $z_c$ and attitude. This implies that the location of each $i$-th drone can be defined in a 2D space $S$ as $p_i = [x_i, y_i]^T$ with respect to an inertial frame $O_T$ as represented in Fig. 1. Hence, the dynamics of each drone is defined as $p_i = u_i, \forall i \in [1, N]$, where $u_i \in U \subseteq \mathbb{R}^2$ is the control velocity input to be designed.

We assume that the target scenario (i.e. the field to be reconstructed using SFM techniques) is contained into an a-priori known, compact set $B \subset \mathbb{R}^3$, containing the ground surface. Then, the objective becomes to observe each point in the target field $B$ from rich viewing angles. This means that for the 3D map reconstruction we need to capture images of the target field $(x_j, y_j, z_j) \in B$ from various $\theta_{h}^{(j)}$ and $\theta_{v}^{(j)}$ angles. In particular, $\theta_{h}^{(j)} \in [\pi, \pi]$ is defined as the horizontal angle and $\theta_{v}^{(j)} \in (0, \pi/2]$ is the vertical angle. Hence, the angle-aware coverage problem targets the coordinated region $Q_c = \{q_j = [x_j, y_j, z_j, \theta_{h}^{(j)}, \theta_{v}^{(j)}]^T, \forall j\}$, which represents the target virtual field. Then, given the mapping $\zeta : Q_c \rightarrow S$, we have

$$q_j \mapsto [x_j - (z_c - z_j) \tan (\frac{\pi}{2} - \theta_{v}^{(j)}) \cos \theta_{h}^{(j)} \frac{\pi}{2} - \theta_{v}^{(j)} \sin \theta_{h}^{(j)}].$$

The monitoring performance for the $i$-th UAV with respect to the point $q_j \in Q_c$ is modeled by the distance between $p_i$ and the monitoring position $\zeta(q_j)$. In particular, the performance function $\ell : P \times Q_c \rightarrow [0, 1]$ is defined as
where $\sigma > 0$ is a tuning parameter that depends on the sensor feature such that $\ell$ is small enough $\forall q_j \in Q_c$.

### 2.3 Objective function and controller design

The next step consists in discretizing the 5D field $Q_c$ into a collection of $M$ 3D cells, i.e. polyhedra of same area $A$, obtaining the new set $Q = \{q_j\}_{j=1}^M$. Let us assign to each $i$-th cell an importance index $\phi_i \in [0, \infty)$, which should decay if $q_i$ is monitored by one of the UAV and for which the decade rate depends on $\ell$. Then, we can define the following update rule for the importance index $\phi_i$ as

$$\dot{\phi}_i(t) = -\delta \max_{i=1,N} \ell(p_i,q_i)\phi_i(t), \quad \phi_i(0) = \phi_i(0),$$

which renders each $\phi_i$ monotonically decreasing. Then, the control objective becomes to minimize an aggregate cost function $J = \sum_{i=1}^M \phi_i A$ to optimize the quality of the images collected by drones driving the cost $J$ towards zero. Moreover, to enhance the mission efficacy, a secondary objective is introduced to shape the UAVs behavior according to $\phi_i$:

- the drone shall escape from region with small $\phi_i$, which corresponds to well-observed point $q_i$, the drone shall escape from this region;
- the UAV shall slow down and remain close to regions with large $\phi_i$.

This concept can be formalized as in Shimizu et al. (2021) introducing a partition of the sampling set $M$ as

$$V_k(p) = \{i \in M | \|p_k - \zeta(q_i)\| \leq \|p_i - \zeta(q_i)\|, \forall i \in [1,N]\},$$

and then describing the cost function rate as

$$\dot{J} = \sum_{i=1}^m \dot{\phi}_i A = -\sum_{\xi=1}^N I_\xi,$$

with the metric $I_\xi$ defined as $I_\xi = \sum_{i \in V_k(p)} \delta\ell(p_z,q_i)\phi_i A$.

This switching mode is enforced into the QP-based controller by taking: i) $h_\ell(p_i,q_i) = \zeta(x_i) - \gamma$, with a given $\gamma > 0$, as a candidate ZCBF; ii) $u_{\text{nom}} = 0$; and iii) softening the constraints with the introduction of a slack variable $w_\xi$. The final QP problem becomes

$$(u_\xi^*, w_\xi^*) = \arg\min_{u_\xi, w_\xi} \epsilon\|u_\xi\|^2 + |w_\xi|^2$$

s.t. $h_\ell + \alpha(h_\ell) \geq w_\xi$.

This QP-based controller results hard to be implemented and solved in real time since the cardinality of $Q_c$ tends to be very large. To address this issue, in Shimizu et al. (2021), the drone field $P$ was discretized by a collection of $\ell$ polygons $A_\ell$, all of the same area $A$, and corresponding gravity points $X$. Then, according to the compression of $Q$ onto $X$ by the mapping function $\zeta$, in Shimizu et al. (2021) the importance index $\phi$ was compressed onto $\psi_\ell \in [0, \infty)$ as

$$\psi_\ell = \sum_{i \in M s.t. \zeta(q_i) \in A_\ell} \phi_i.$$
to guarantee a forward and side overlap between adjacent images greater than 80%. The resulting ground sample distance (GSD) and the field of view (FOV), at 35 m of altitude, were equal to 1.75 cm pixel and 22.4x16.8 m, respectively. Image correction and true reflectance ratios calculation have been performed thanks to the incident light sensor (ILS), mounted on the top of the drone, which measure the ambient light level for each shot in each band. In addition, geometric correction, co-registration (or stitching) and radiometric correction was done by MAIA images software (MultiCam Stitcher Pro). Finally, the multi-spectral map of the whole orchard has been obtained by processing the image block with Agisoft Metashape (2020) software. Using the position of six ground markers (in-field determined with a differential GNSS), the map was also georeferenced in the WGS84 EPSG:4326 reference system.

The procedure to retrieve the priority map from the multi-spectral ortho-mosaics is based on 3 main steps: 1) the semantic interpretation by a convolutional neural network approach; 2) a refinement by morphological operations; and, finally, 3) a filtering and rescaling task. Pixels representing the crop canopy within the multi-spectral imagery are thus detected by a properly trained U-Net convolutional neural network (Mathworks Matlab®, 2020) and reported in a categorical map (see Fig. 3(b)). To train, validate and test the U-Net, the ortho-mosaic was processed to select three different subsets of pixels, as described in Comba et al. (2021). The raw categorical map provided by the U-Net (Fig. 3(b)) was then processed with a sequence of morphological operators, in order to remove noise and small objects from the map, and to refine crop canopies boundaries (Fig. 3(c)). In particular, the sub-sequentially performed operations are a closing and an opening operation, with a circular flat morphological structuring element with radius equal to 5 and 10 pixels, respectively. Then, to properly eliminate sharp gradient between clusters, an averaging filter with circular kernel was adopted (Fig. 3(d)). The final priority map is represented in Fig. 4 and used as the initial distribution of the importance index $\phi^{(0)}$ for the covering control strategy as described in the following section.

4. NUMERICAL SIMULATIONS

In this section, we describe the preliminary results obtained applying the proposed approach to an apple orchard. In the selected frameworks, we assume to cover the selected area with $N = 3$ drones, whose initial positions were selected as $p_1 = [5.0, 0.5]^T$, $p_2 = [7.5, 0.5]^T$, and $p_3 = [10.0, 0.5]^T$, to cover the selected orchard. The local controller allowed to maintain a relative altitude of 10 m with respect to the terrain while the UAV velocity is constrained into the input space $U = \{ u \in U | |u| \leq 5 \}$, limiting the drones acceleration to less than 5 m/s$^2$. The other controller parameters were set as summarized in Table 1. In particular, $\sigma = 1$ allowed to drive $h \to 0$ at 3.5 m, which is the orchard inter-row space, while $\gamma = 5000$ set the drone velocity around 2 m/s when monitoring high-importance region.

From the priority map, retrieved as described in Section 3 and depicted in Fig. 4, we can observe how the importance

Fig. 3. (a) Zoom-in of the orchard; (b) raw categorical map; (c) refined map; and (d) final priority map.
The next step consisted in validating the proposed covering control algorithm in a ROS environment, where CVXOPT was used to solve the QP of the proposed controller with an update frequency of 20 Hz. In Fig. 5, we reported some frames from the simulation interface where it is possible to observe the evolution of the performance index $\psi$ according to the field coverage performed by the drones. In each frame, we can observe also the importance function $\phi$ with respect to the viewing angles for some specific check points. The drones took around 4 minutes to cover the field and to collect the images from the selected viewing angles. In the second frame of the upper row of Fig. 5 we can observe the collision avoidance strategy that makes the drones move away each other. On the other hand, in the third frame we can observe how the two drones on the right follows the priority map to collect images along the rows. Then, in the lower row of frames, it is possible to observe how progressively the drones covered the entire area from rich viewing angles, achieving the primary objective.

Fig. 5. The use of UAVs in monitoring yellow sigatoka banana. biosystems engineering, 193, 115–125.

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### 5. CONCLUSION

In this paper, we applied a customized covering control strategy, that takes into account rich viewing angle to reconstruct 3D maps of an apple orchard. The proposed scheme was based on the preliminary extrapolation from a multi-spectral map of a priority field $\phi$ using a semantic interpretation approach. This allowed to determine the area of higher interest for the map reconstruction, coinciding with the crop rows. The effectiveness of the proposed scheme was finally demonstrated through numerical simulations.

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Fig. 5. Evolution of the importance function $\psi$, where red circles denote the UAVs field of view. The circles at the bottom of each figure show the importance function $\phi$ with respect to viewing angles $(\theta_h, \theta_v)$ of the following coordinates triplets: [10, 20, 0], [10, 40, 0], [21, 30, 0], [28, 60, 0], [46, 80, 0], [49, 10, 0].

Fig. 6. (a) Time series of the objective function $J$. (b) Time series of the UAVs’ velocity $\|\dot{\mathbf{p}}_1\|$ (red) and $J_{\text{near}}$ (black).

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