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UAV Position Tracking with Ground Cameras †

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Abstract

The use of Unmanned Aerial Vehicles (UAVs) has become quite popular in several applications during the last few years. Their spread is motivated by the flexibility of usage of UAVs and by their ability to automatically execute several tasks, mostly thanks to the availability of Global Navigation Satellite Systems (GNSSs), which usually allow reliable outdoor localization of aerial vehicles. However, the extension of task automatic execution indoors, and in other challenging working conditions for the GNSS, requires an alternative positioning system able to compensate for the unreliability or unavailability of GNSS in those cases. To this end, additional sensors are usually considered. Among them, cameras are probably the most popular ones. The most common case of a vision-based positioning system is a camera mounted on a moving platform used to determine its ego-motion in a dead-reckoning approach, i.e., visual odometry. Although this solution is affordable and does not require the installation of any infrastructure, it enables absolute positioning of the camera, i.e., of the UAV, only if certain landmarks, with known position, are visible in the flying area. In contrast, this work considers the use of external cameras installed in the flying area to track the UAV movements. This approach is similar to the one implemented in motion capture systems as well, where a set of static cameras is used to triangulate some target positions using calibrated cameras. Instead, this work investigates the use of vision and machine learning tools to (i) extract the UAV position from each video frame and (ii) estimate its 3D position. Estimation of the 3D UAV position is performed with a single camera, exploiting machine learning tools in order to avoid the need for camera calibration. Performance analysis is provided for a dataset collected at the Agripolis campus of the University of Padua.

Keywords: indoor positioning; collaborative positioning; UWB; smartphones

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1. Introduction

Thanks to their usage flexibility and affordable cost, Unmanned Aerial Vehicles (UAVs) are nowadays used on a very wide range of outdoor applications. Since they are often used in automatic flight mode, the availability of a reliable positioning and navigation system is usually a *sine qua non* requirement: this typically means the need for the Global Navigation Satellite System (GNSS) positioning to work properly. However, the quest to extend their usability, even in conditions where accurate GNSS positioning is not available, motivated the development of alternative positioning systems. Such systems are typically based on the integration of information provided by different sensors, such as cameras [1], LiDAR [2], ultrasound [3], UWB [4] and RADAR [5,6], even exploiting multi-platform communication and localization when possible [7,8].

Among the alternative sensors, cameras have been largely used, both for their affordable price and because of their multiple uses, e.g., when mounted on a UAV they can be used for mapping as well. As a matter of fact, in Geomatic applications, the most common use of cameras mounted on UAVs is mapping. An alternative, which has recently become quite popular, is the use of a camera to determine the UAV motion and to simultaneously map the surrounding environment in a visual Simultaneous Localization and Mapping (SLAM) approach [9,10]. Sometimes, SLAM-like algorithms exploit additional information as well to enhance localization performance [11]. Vision-based absolute positioning with a camera mounted on a drone is feasible only by providing some additional information, typically using some landmarks, targets, and ground control points in aerial photogrammetry. Alternatively, cameras installed in the flying area can be used for monitoring and localizing the UAV. These working conditions, which are quite similar to those of motion capture [12], typically require the usage of multiple cameras to properly track the UAV movements [13,14].

Landing on small areas when accurate GNSS is not available or reliable is an important example of the need for alternative sensors to support precise navigation [15,16]. In addition to this application, the working conditions considered in this work can be compatible with those related to UAV monitoring in surveillance applications. In such cases, several sensors have already been considered, including RADAR [17], acoustic arrays [18], cameras and other sensors [19,20]. Given the increase in aerial incidents caused or induced by UAVs, for instance, close to airports, a number of studies have been already published in the literature for drone detection and monitoring [21,22].

When based on cameras, UAV detection has been mostly based either on background–foreground extraction methods [23], where the background is usually assumed to static or almost static, or on deep learning methods [24], often by means of YOLO (You Only Look Once) networks [25,26]. In addition to UAV detection, artificial intelligence methods can also be exploited for a number of UAV-related additional tasks, as summarized in [27].

Similarly to motion capture and to monitoring applications, this work considers the use of an external camera installed in the flying area to track UAV movements. However, differently from motion capture, and other multiple-camera systems [13], in this work, only *one uncalibrated camera* was employed to determine the 3D position of the UAV. Furthermore, while in standard monitoring and patrol systems several PTZ (pan, tilt, zoom) cameras are usually employed to properly cover the area of interest, in this case, only one static camera was used. Also, differently from the case of cameras mounted on the UAV [14], the system proposed in this work allows for the absolute position of the UAV to be determined, without the need to install additional targets or any further information on the environment. UAV detection on the camera imagery is implemented similarly to other UAV monitoring applications, thanks to computer vision tools. However, the 3D position of the UAV is determined by using machine learning tools to implicitly assess the camera–UAV distance

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or, equivalently, the scene depth and scale by using just a camera frame. The proposed method and the dataset used to validate it are presented in the following section, whereas the initial results of our investigation are shown in Section 3. Finally, some conclusions are drawn in Section 4.

2. Materials and Methods

The proposed method is based on the usage of a fixed ground camera, even if it could be extended to the use of multiple cameras. Tests to assess its performance on a real-case scenario were conducted on a dataset collected at the Agripolis campus of the University of Padua by a joint team of researchers within the IAG (International Association of Geodesy) Working Group 4.1.5 "Wireless positioning with terrestrial instruments". Figure 1 shows the considered UAV, a DJI Matrice 210 (DJI, Shenzhen, China), while flying over the test area, whereas Figure 2 shows both the track of the UAV during the test and the location of the camera used for tracking it. The camera was a Sony alpha ILCE-5100 (Sony, Tokyo, Japan; video resolution 1440 × 1080 pix, at 25 Hz) mounted on a tripod. The camera mounted the standard 16–50 mm lens, with focal length fixed to 16 mm during the test. Even if using such a focal length value is not a must, ensuring a large field-of-view may help for tracking the UAV in a large area. The video acquired by the camera was stored in mp4 format and processed offline even though, potentially, the proposed method could be considered for real-time applications. The camera was geometrically and radiometrically uncalibrated. UAV positions shown in Figure 2 were collected by a GNSS receiver in NRTK (Network Real-Time Kinematic) mode at 5 Hz. It is worth noting that the closest permanent station of the network was less than 100 m from the UAV, hence ensuring good quality corrections. The UAV flew for approximately 15 min, and only fixed solutions were used as a reference. UAV positions, measured by the GNSS receiver, were first projected with (UTM-ETRS89), and then the projected coordinates were locally shifted, moving the origin close to the flying area, in order to make them more easily readable. The corresponding Easting, Northing and Up coordinates were used as x, y, z coordinates to describe the UAV positions in the training and test phase of the proposed method. During the test, the camera–UAV distance varied from a minimum of approximately 24 m to ≈94 m.



Figure 1. DJI Matrice 210 flying during the test. While acquired from close to the ground, this image was not collected by the Sony alpha ILCE-5100 camera used in this work.

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A basic assumption of the developed method is that of the UAV visibility: UAVs operating BVLOS (beyond visual line of sight) cannot be tracked by the proposed method. The scene was mostly static, with a few dynamic objects, including some birds and clouds.

The proposed workflow is summarized in Figure 3. Similarly to [23], the almost static background is exploited to detect UAVs through background subtraction. Nevertheless, it is worth noting that YOLO networks can also be used to generalize this step [25,26]:

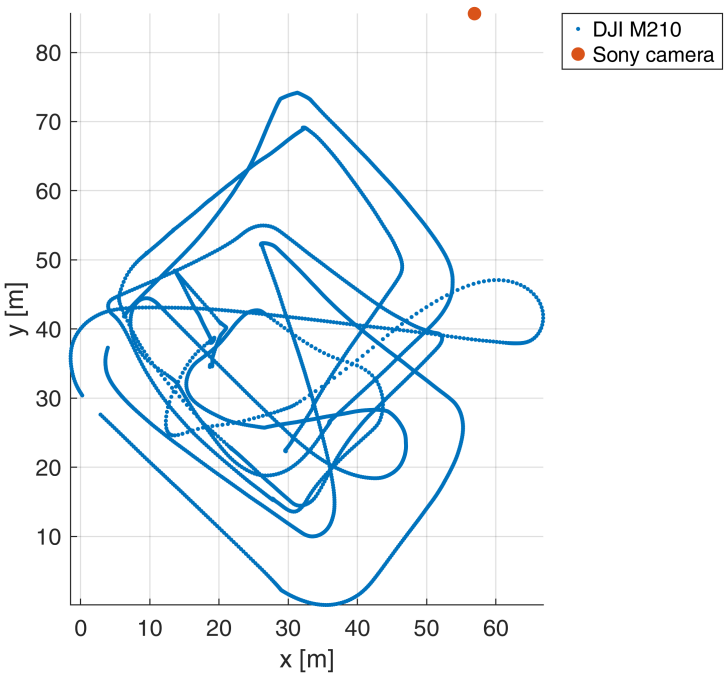


Figure 2. Track of DJI Matrice 210 during the test (blue dot marks) in UTM32 coordinates, locally shifted, and Sony camera position (red solid mark).

- Dynamic object detection via background subtraction. A threshold is applied on the difference between the current frame and a past one in order to determine the moving parts of the scene.
- UAV detection by restricting the allowed area sizes and imposing a regular trajectory. To be more specific, the following conditions were checked to limit the detection to flying objects of size similar to UAVs:
  - Object area on the image plane within minimum and maximum thresholds. Among the connected regions extracted from the background difference, only those within two properly selected minimum and maximum area threshold were kept.
  - Distance of the object centroid within a maximum threshold from Kalman filter prediction. A Kalman filter on the image plane was used in order to obtain an approximate prediction of the next UAV position on the image: Only objects within a properly selected threshold from such a position were kept. Only the closest one was maintained when two or more options were present to continue a UAV trajectory.

Concerning the features used to characterize the position information on the UAV on each frame, the centroid and the size of the area of the UAV on each image frame were considered. Intuitively speaking, the centroid of the region on the image plane corresponding to the UAV provides a direction, with respect to the camera reference frame, that the UAV should be on that instant. The most critical aspect when using only one camera to assess the UAV position is probably determining the camera–UAV distance, which is

clearly related to the scene depth (and scale) estimation. In the considered framework, the size of the area of the UAV on the image should provide the complementary information in order to determine the UAV distance from the camera. Hence, potentially, the combination of the UAV centroid and area size should be sufficient to assess its 3D position. When knowing the camera interior and exterior parameters, such computation can be done by taking into account the geometric camera model. Instead, in this work, a non-calibrated camera is used, and the UAV 3D position is inferred by means of machine learning-based data regression (last step in Figure 3).

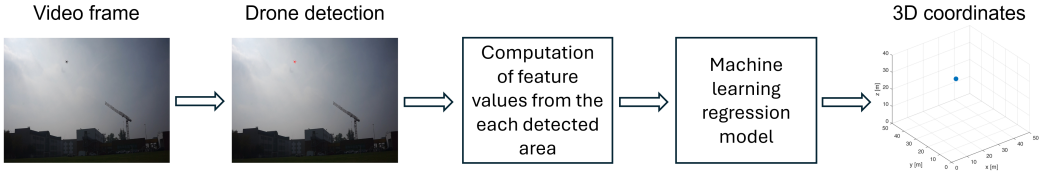


Figure 3. Workflow scheme, followed to determine the UAV 3D coordinates (blue dot in the image on the right) from.

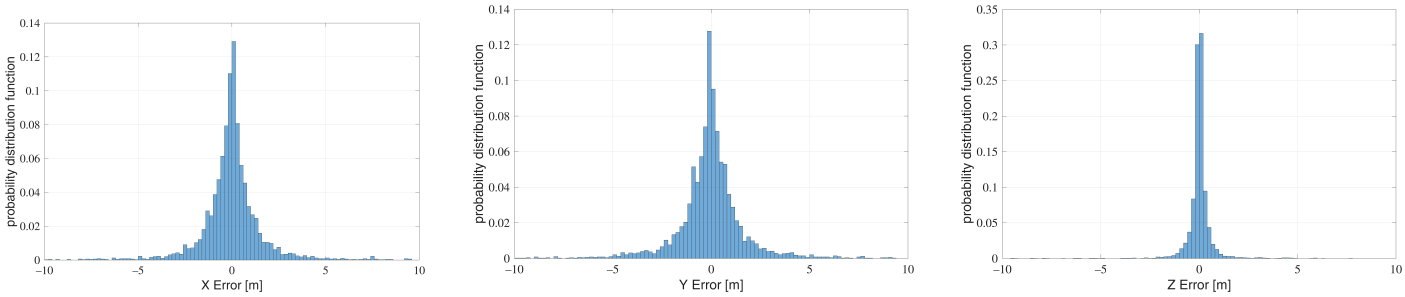
To be more specific, at each frame three ensemble regression models were used, each to assess one of the coordinates of the UAV. The coordinates of the centroid of the UAV on the image plane and its area are considered as inputs for each of such regression models. As outputs, the UAV UTM coordinates, locally shifted, were separately used. Among the approximately 16 k frames where the UAV was visible in the acquired dataset, 11 k random frames were selected as learning dataset, whereas the remaining 5 k ones were used in the test dataset. The training resulted in ensemble regression models, composed of 100 regression trees aggregated by means of the Least Squares Boosting algorithm, able to predict the UAV position with virtually zero mean error along the x, y, z directions, and Median Absolute Deviation (MAD) of a few decimeters. The results on the test dataset are shown in the following section.

3. Results

The distributions of the 3D positioning error values along the x, y, z directions for the test dataset are shown in Figure 4. Table 1 reports the statistics of the error on both the learning and test frames: the average (mean) value of the error, the MAD of the error, standard deviation (std) of the error and the 70° percentile along each of the 3 axes. Since the x, y, and z axes are aligned with the UTM coordinates, just locally shifted, errors shown in the figure and in the table are actually along the East, North, and Up directions. The errors on the learning dataset are slightly smaller than those on the test dataset, but they are of the same order of magnitude. The errors appear to be unimodal and quite well centered around the zero, as confirmed by their means ($\leq$4 cm on each axis), shown in Table 1. Considering the results on the test dataset, deviation (MAD) with respect to their mean values was apparently at sub-meter level, ranging from 13 cm for the z axis to approximately half a meter for the other two axes (Table 1). As for the standard deviation of the error, its values are higher than the MAD ones because of some errors at relatively high values (std is more sensitive to outliers than MAD). Finally, the 70° percentile (which, for instance, is supposed to be slightly larger than 1σ in Gaussian distributions) values are smaller than the MAD ones.

Despite a vision-based positioning error intuitively depending on the camera–UAV distance (the higher the distance the higher the error), Figure 5 does not clearly show such a dependence. This proves that other factors, probably in particular due to the implemented machine learning method, are currently dominant with respect to the vision resolution one, hence showing the potential for some future improvements in the obtained results.

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(**a**) (**b**) (**c**)

Figure 4. Distribution of the positioning error on the test dataset along: the (**a**) x, (**b**) y, and (**c**) z axes.

Table 1. Statistics of the 3D error on the assessed UAV positions on the learning and test frames.

	x [m]	y [m]	z [m]
learning dataset			
mean	0.00	0.00	0.00
MAD	0.52	0.57	0.12
std	1.47	1.47	0.42
70° percentile	0.36	0.40	0.09
test dataset			
mean	−0.04	0.02	0.00
MAD	0.56	0.64	0.13
std	2.52	2.45	0.81
70° percentile	0.38	0.43	0.10

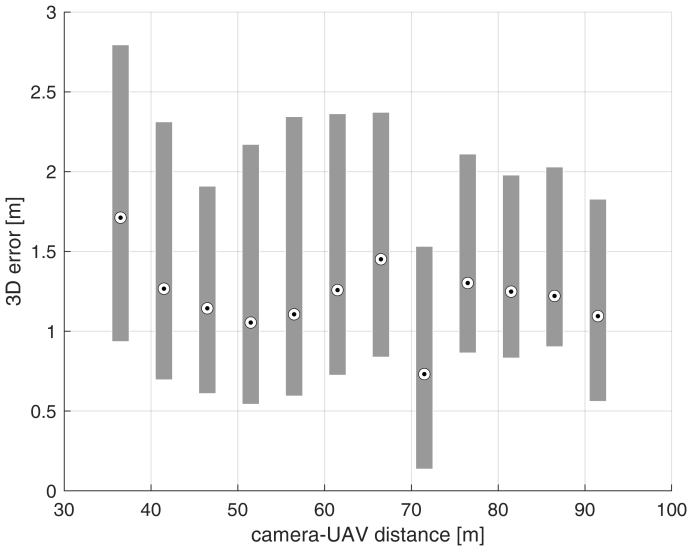


Figure 5. Box plot of the 3D positioning error as a function of the camera–UAV distance. The central marks indicate the median errors, whereas the 25th and 75th percentiles are indicated by the bottom and top edges of the boxes.

Finally, Figure 6 compares a portion of the reference (red dot marks) and estimated (blue dot marks) UAV trajectories. The comparison shows that the estimated trajectory is clearly much more irregular, as expected, given that such estimates are currently generated by independently considering each frame in the test dataset. Hence, exploiting the regularity of UAV movements, for instance, using a Kalman filter, is expected to improve the obtained results.

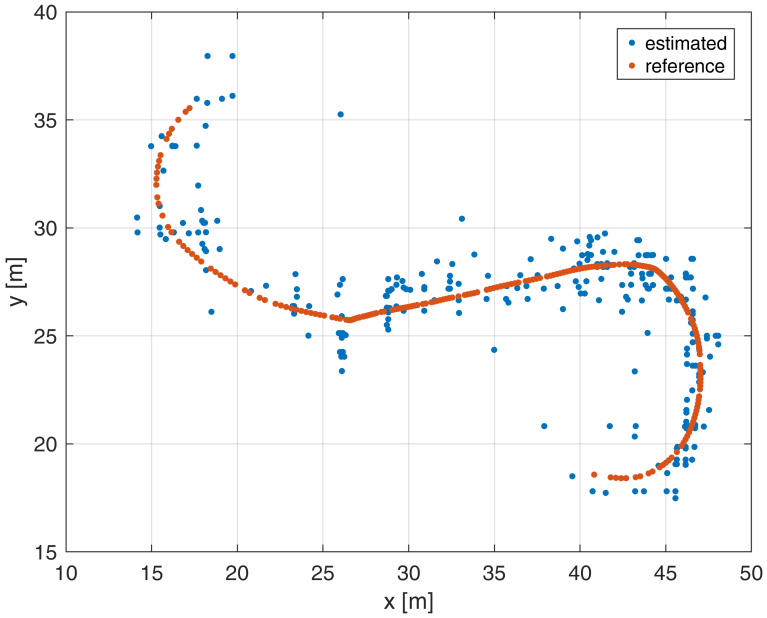


Figure 6. Comparison between a portion of the reference (red) and estimated (blue) UAV trajectories.

4. Discussion and Conclusions

The implemented machine learning-based positioning method uses a single ground camera, geometrically uncalibrated, to track a UAV while it is visible on the camera video frames. The positioning error, obtained in the initial investigation presented in this paper, is close to zero on average ($\leq$4 cm on each axis), while its median absolute deviation is at sub-meter level: approximately half a meter along the x and y directions, 13 cm on the z.

Figure 5 does not show any clear increase in the error with respect to the distance. Such behavior shows that other factors, such as the implemented machine learning-based regression method and the UAV detection on the image plane, are currently dominant with respect to the error due to the camera spatial resolution.

In terms of potential future improvements, the temporally irregular behavior of the estimates reported in Figure 6 shows that a possible improvement of the proposed method is the use of Kalman filtering for temporally regularizing the trajectory.

Concerning the machine learning-based regression, possible improvements can be obtained by introducing additional features as inputs or by investigating different regression models, including using deep learning-based methods. Regarding the latter, it is, however, worth noticing that the implemented method requires less data and computational power with respect to deep learning methods, thanks to the fact that we manually introduced information that should be sufficient for solving the problem (despite some redundant additional information could be useful). Nevertheless, deep learning could ensure a higher ability to properly describe the input–output relation.

The current results are based on the implicit hypothesis that the UAV size is similar to that used in the learning dataset. Generalizing on UAVs of any size may require the recognition of the UAV type, or equivalently of its real size. Despite deep learning methods having already been used for UAV classification [21], it is quite clear that such a classification task is reasonably feasible only when the camera–UAV distance is not too large.

Future works will include enlarging the dataset size; tests with different UAVs; the use of neural networks, such as YOLO v11, for UAV detection and classification; the integration of information from other sensors; the use of multiple cameras; and the use of high-resolution cameras (the camera used in this work has a resolution of $\approx$1 k, whereas, nowadays, many cameras on the market reach 4 k, or even more). Furthermore, while the usage of a geometrically uncalibrated camera makes the system less expensive and easier

to set, the usage of multiple geometrically calibrated cameras shall enhance the obtained results, as will be studied in our future investigations.

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