Aerial Robotics in Building Inspection and Maintenance

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Buildings need periodic revision about their state, materials degrade with time and repairs or renewals have to be made driven by maintenance needs or safety requirements. That happens with any kind of buildings and constructions: housing, architecture masterpieces, old and ancient buildings and industrial buildings. Currently, nearly all of these tasks are carried out by human intervention. In order to carry out the inspection or maintenance, humans need to access to roofs, façades or other areas hard to reach and otherwise potentially hazardous location to perform the task. In some cases, it might not be feasible to access for inspection. For instance, in industry buildings operation must be often interrupted to allow for safe execution of such tasks; these shutdowns not only lead to substantial production loss, but the shutdown and start-up operation itself causes risks to human and environment. In touristic buildings, access has to be restricted with the consequent losses and inconveniences to visitors. The use of aerial robots can help to perform this kind of hazardous operations in an autonomous way, not only teleoperated. Robots are able to carry sensors to detect failures of many types and to locate them in a previously generated map, which the robot uses to navigate. Some of those sensors are cameras in different spectra (visual, near-infrared, UV), laser, LIDAR, ultrasounds and inertial sensory system. If the sensory part is crucial to inspect hazardous areas in buildings, the actuation is also important: the aerial robot can carry small robots (mainly crawler) to be deployed to perform more in-depth operation where the contact between the sensors and the material is basic (any kind of metallic part: pipes, roofs, panels…). The aerial robot has the ability to recover the deployed small crawler to be reused again. In this paper, authors will explain the research that they are conducting in this area and propose future research areas and applications with aerial, ground, submarine and other autonomous robots within the construction field.

***Keywords**: Building Inspection – Building maintenance – Failure detection – Aerial robots*

INTRODUCTION

In this paper, authors will explain the possibilities and benefits of using aerial robots in applications related with building construction and maintenance through a serial of steps that have been followed in a present and real project. It is proposed the development of the first aerial robotic system with multiple arms and advanced manipulation capabilities to be applied in inspection and maintenance activities in industrial plants.

The motivation of this proposal is to avoid dangerous and costly work in activities such as the taking measurements that require contact and installation of sensors in inaccessible locations, during repairing operations and the deployment of mobile robotic systems enabling these robots to operate longer performing large area inspection without the need of human intervention in these inaccessible locations.

The objectives of the proposal are:

1. Research and development of aerial manipulation methods and technologies required to perform the building inspection and maintenance, with:
   - Aerial robotic manipulation for inspection and maintenance. The objective is to improve the operational conditions and robustness of the existing aerial manipulation methods and technologies, and their integration in an aerial robotic manipulation system to perform the inspection and maintenance applications.
   - The objective is the development of a multirotor platform that can fly and manipulate with the coordinated motion of the arms. The operation with two arms is useful in applications such as pasting a tape for isolation, or to provide a fixed contact point with one arm while operating with the second arm.
2. Validation of the technologies developed in a real environment, residential or industrial buildings:
   - Taking measurements that require physical contact while flying.
   - Installation and maintenance of permanent Non Destructive Tests (NDT) sensors on remote components such as pipe works, fire flares or structural components. This application assumes the existence of appropriate housing for the sensor to allow a mounted fixation by dexterous handling.

Another interesting application for this project, and other real examples, is the deploying a mobile robotic system permanently installed on a remote structure. Assuming the presence of a newly designed mobile robot the application consists of the use of the aerial robot to deploy the robot in the structure without costly and dangerous human operations.

These general objectives above are developed following the next Sections in the paper.

Control of aerial robots with multiple manipulation means

This task deals mainly with dynamic modelling and control of aerial platforms with multiple arms. In the first period of activity several research activities have been done. First, a general dynamic model of a multirotor UAV (unmanned aerial vehicle) with multiple arms having compliant joints have been developed. Furthermore, three different phases have been identified in a typical mission with an aerial manipulator, (Fig. 1): 1) take-off/landing and flight mode, in which the arms are not moving; 2) approaching mode, in which both the UAV and the arms are controlled in position but without contact; and 3) operational mode, in which there is physical contact of the arms with the environment and application of forces.

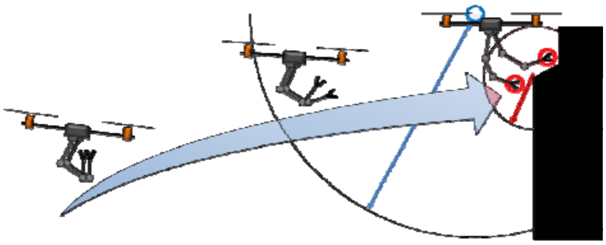

Fig.1. Phases in a typical mission with an aerial manipulator.

Finally, the aerodynamics effects of the multirotor flying very close to surfaces have been further studied. Different cases where the full multirotor, only one rotor and only three rotors are under the ground effect (proximity to a flat surface), and when the multirotor is flying close to pipes have been analyzed and tested experimentally in the test bench (Fig. 2). Then a map of aerodynamic forces in the environment has been developed, in which at each possible position of the aerial manipulator in the map, the additional forces and torques generated by the aerodynamic effects are included in the map, with the objective of being used in the UAV controller as a feedforward term, and in reactive trajectory replanning. Wind disturbance is not a serious problem under 30mph unless the drone decides to land.
Several developments have been done in the different phases. A method to detect contact of the arms with the environment (change between phases 2 and 3) has been developed based on reference[1] using the dynamic model and the compliant joints to measure torque in the joints, which also provides an estimation of the contact forces and torques. A robust nonlinear control strategy for the whole aerial manipulator has been also developed for phases 1 and 2, and tested in simulation. It is now being modified to also control the aerial manipulator in phase 3. Furthermore, a force control strategy for the compliant arm has been developed and tested, based on a joint level impedance controller[2]. At UPC, a servoing scheme has been developed using numerical optimization to obtain the commands for the actuators[3].
In this task, a trajectory generation approach using quadratic programming is described for aerial manipulation, i.e. for the control of an aerial vehicle equipped with a robot arm. An overall scheme of the software architecture is depicted in Figure 3.

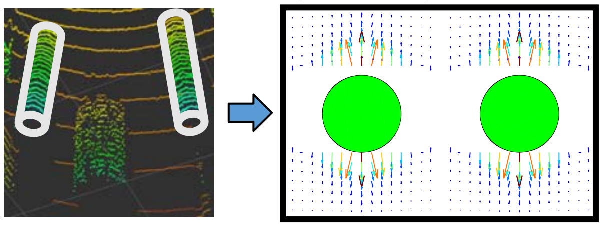

Fig.2. Example of aerodynamics map: two pipes are detected online with the UAV sensing system, and a map of the aerodynamic effects that the UAV would undergo if it were placed at each point in the map grid. The arrows in this figure mark the increment in thrust force due to aerodynamic interference of the rotors' airflow with the pipes.

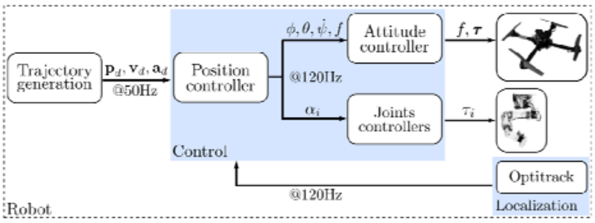

Fig.3. Overview of the architecture pipeline for the trajectory generation approach and UAM (unmanned aerial manipulator) control with all algorithms running on board.

The proposed approach applies the online active set strategy to generate a feasible trajectory of the joints, in order to accomplish a set of tasks with defined bounds and constraint inequalities. The definition of the problem in the acceleration domain allows integrating and performing a large set of tasks and, as a result, to obtain smooth motion of the joints. Moreover, a weighting strategy, associated with a normalization procedure, allows to easily defining the relative importance of the tasks.
The performance of the proposed technique has been demonstrated through real experiments with all the algorithms running onboard in real time. In particular, the aerial manipulator can successfully perform navigation and interaction phases, while keeping motion within prescribed bounds and avoiding collisions with external obstacles. A hybrid image-based and position-based visual servoing is presented, allowing keeping together the main benefits of classical image- and position-based approaches in a common control framework. In fact, the presence of redundancy in a UAM system allows combining a number of elementary tasks with the new hierarchical task formulation proposed in this paper.

PERCEPTION FOR ROBOTIC MANIPULATION IN AERIAL OPERATIONS

The objective of this step is the Identification of targeted objects (e.g. structural elements in a building) and in estimating the aerial vehicle pose using vision.

Interactive and Online Object Recognition

The detection and tracking of an object using vision requires advanced techniques that adapt over image changes, for example due to illumination variations. In that sense, UPC has worked on a fast and online approach that progressively learns multiple object classifiers using scanty human supervision. More in detail, in the proposed method[4], an inspection operator just needs to annotate a small fraction of frames from a given video stream (e.g., provided by a camera attached to the aerial platform) to compute object specific classifiers based on random Ferns which share the same image features. The resulting methodology is fast (in a few seconds, complex object appearances can be learned), versatile (it can be applied to unconstrained scenarios), scalable (real experiments show we can model up to 30 different object classes), and minimizes the amount of human intervention by leveraging the uncertainty measures associated to each classifier.

In order to learn multiple models we propose computing simultaneously and in parallel multiple classifiers, one for each object class, and with specific configurations like the spatial distribution of ferns or the particular object size. This method is scalable for multiple objects since each object is learned independently at the time in which the operator selects a new object model in the video stream. This allows learning and detecting up to 30 object classes in an eficient and dynamic manner.

UPC has validated the approach on synthetic data and on real sequences including industrial scenarios, as for the case of inspecting a pipe welding or a pipe fissure, shown in Figure 4. Moreover, in reference[5] is shown that with little human assistance, we are able to build object classifiers robust to viewpoint changes, partial occlusions, varying lighting and cluttered backgrounds.

Real-time pose estimation based on natural landmarks (P0P)

Physical interaction with the environment calls for positioning accuracy at the centimeter level, which is difficult to achieve in most industrial scenarios where GPS is not available. Moreover, not only a precise pose estimation is strictly required but also the sensors to obtain it have to consider some constraints in terms of weight and power consumption. Considering these restrictions, a good option is the use of visual information (i.e., cameras).

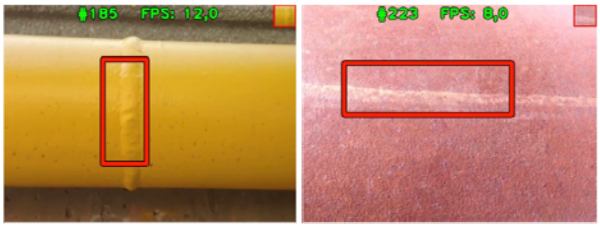

Fig.4. Examples of the online object recognition method running in two inspection use cases.

With regards to this pose estimation using local information provided by a camera, UPC has developed a new featureless pose estimation method[6] that, in contrast to current Perspective-n-Point (PnP) approaches, it does not require n point correspondences to obtain the camera pose, allowing for pose estimation from natural shapes that do not necessarily have distinguished features like corners or intersecting edges. Instead of using n correspondences (e.g., extracted with a feature detector) the raw polygonal representation of the observed shape is used to directly estimate the pose in the pose-space of the camera. Thus, this approach, called Planar PØP, extracts the pose of the UAV using only contours of natural shapes instead of feature descriptors, and without the need for artificial markers.

It consists of 4 steps: 1) initialization, to find a starting location to align the contours; 2) contour alignment, to look for the best homography alignment in the Homography-space; 3) pose extraction from the homography, to compute a first estimation of the pose using a novel method named Virtual Correspondences (VC); and 4) pose refinement in the pose-space.

An example of the proposed pose estimation method is shown in Figure 5, where a quadrotor with a camera attached (pointing downwards) is localized. Notice how the detected figure in the floor is in this case synthetic but has no corners or texture.

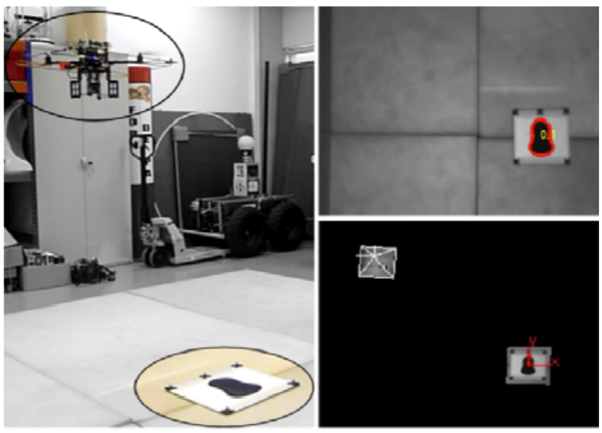

Fig.5. Pelican robot flight. Right: shape detection and camera pose provided by the UPC featureless pose estimation method[6].

Generalized pipe detection

Pipes and tubes are common structures in building environments, thus detection and recognition of pipes is essential for image and scene interpretation. In order to solve the problem without a priori data or human feedback, a generalized pipe detector based on visual has been developed. Notice how this is the most challenging of the above mentioned situations, and how its development can be directly exploited to improve the procedure for the other scenarios.

One of the main physical characteristics of pipes, in terms of image processing, are the edges: even when they present similar hue and texture with respect to the background, the geometry of a pipe is noticeable. Another important characteristic is the material texture, however pipe detections may require computationally expensive approaches.

The approach to detect pipes using visual information initially detects all the straight lines in a region of interest (ROI) using the Hough transform. This ROI is a subset of the original image taken to alleviate the image-processing task (the original frame is considered usable only if prior information or human supervision are available). The Hough transform itself is widely considered the strongest straight edge detector, being robust to discontinuities and partial occlusions. In order to add robustness to illumination changes during the edge detection step, techniques such as the Otsu's threshold can be applied.

In a general detection case, image segmentation operations may require solving ambiguities (Figure 6), making the detection and recognition procedures computationally expensive. To alleviate these procedures, visual servoing techniques are used to track in real-time the edges of a pipe previously found.

it is possible to estimate its pose with respect to optical center of the camera, namely C. To do so, the pipe is modelled as a straight homogeneous circular cylinder (SHCC). Hence, the relative pose between the pipe and C is denoted in 4 DoF, i.e. the orientation of the pipe axis and distance to C. This SHCC can be represented as a degenerate quadric equation expressed in terms of the Plücker coordinates of its symmetry axis (Figure 7). Then, this expression is projected into the image space with the camera projection equations to fit into the apparent contour. This method has been successfully tested in indoor experiments, producing a relative error below 4% for depth estimation. Still, when the camera optical axis and the pipe axis become close to parallel, which constitutes a degenerate configuration, the method becomes inconsistent. Further testing is needed to report more accurate results with industrial-like site datasets.

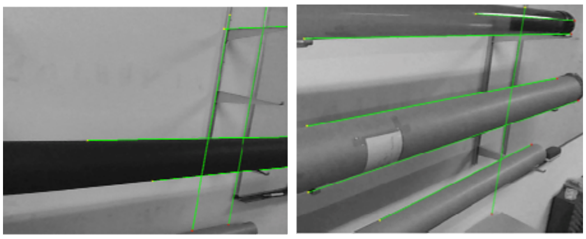

Fig.6. Two samples of Hough transform pipe detection, varied materials. Random elements can be easily present straight edges in structured environments, so the procedure contemplates solving ambiguities exploiting prior data or image processing.

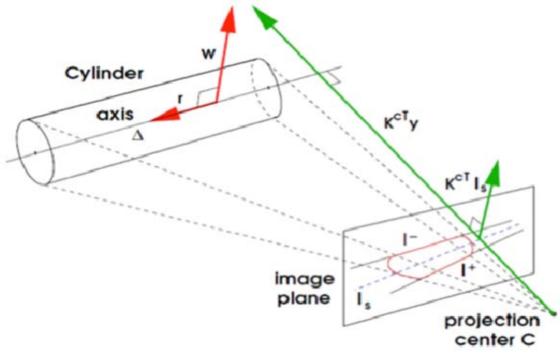

Fig.7. Projection of the apparent contours of a SHCC modelling a pipe in the image plane, with the camera projection center and the pose coordinates, from reference[7].

The design and development of adaptive model-based methods for object detection and estimation have to be considered. Figure 8 shows the scheme of the method designed. There are two stages: the learning stage, which is performed offline and the localization stage, which is perfomed online.

The objective of the learning stage is to train feature-based models that represent the objects of interest to be detected and localized in the scenario. A set of features are extracted from the images and are used to train a feature-based model that represents the object. Features such as SIFT, ORG, SURF among otherswere used.

The models trained should be robust against changes in lighting conditions and against partial occlusions originated by the scenario or by the robot arms during object manipulation.

The objective of the application stage is to use the trained models to detect, identify and localize the object in the scenario.

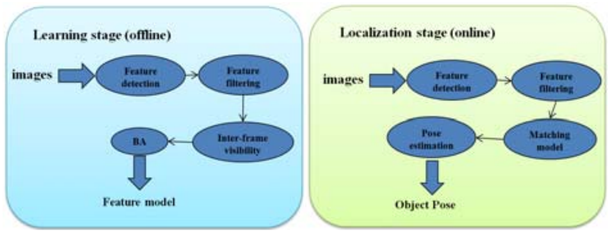

Fig.8. Schemes of the learning and application stages for feature-based modelling for accurate object detection and pose estimation.

PRECISE 3D MAPPING AND LOCALIZATION

The first objective is to build an accurate map of the scenario before the inspection and maintenance tasks are carried out. An augmented map able to integrate information coming from different sources will be developed. Particularly, the integration of visual place recognition, point clouds (provided by 3D cameras or lasers) and range-only sensors will be developed in the project. The augmented map will exploit the synergies of all these sensors, reducing the dependence of a single device for localization and increasing the reliability of the map.

The second objective is to develop a multi-sensor method for accurate 6DoF robot localization. In this task localization is divided in two different parts: 1) localization during navigation and 2) localization during inspection and manipulation.

The work has been the design, development and testing of multi-sensor methods for accurate localization and mapping during robot navigation. Localization is based on using local sensors and a multi-sensor augmented map. The methods developed exploit the synergies between different sensors in mapping and localization:

- Range sensor beacons. Measurements are not very accurate but have ranges of more than 100 m.
- 3D LIDAR. Measurements are point clouds with accurate range-bearing information but the ranges of the sensorin ourdoors are of only 20-25 m.
- Stereo camera system.They provide accurate point clouds but the ranges of the sensor are of only 10-15 m.

When far from obstacles the localization method will be able to localize the robot using only the range sensors. The localization will not be very accurate but will be enough for navigation in spaces with distant obstacles.When near obstacles the localization method will integrate information from the range sensors, 3D LIDAR and stereo camera. The localization will be accurate and the robot will be able to navigation in scenarios with obstacles.

In the generation of a multi-modal enriched map we adopted the approach to perform independent SLAMs for each type of sensors. It provides higher modularity, since the different independently.built maps can be manipulated and joined. It also results in a more efficient solution than a multi-modal SLAM that integrates all measurements.Of course, this approach leads to having to solve the problem of how to join the maps obtained with sensors of different modality. We first address the problem of joining maps obtained with visual information with maps built with range sensor information.

Autonomous state estimation using high-rate low-cost sensors

UPC proposed in reference[8] a simple, low-cost and high-rate method for state estimation enabling autonomous flight of Micro Aerial Vehicles (MAVs), which presents a low computational burden. The proposed state estimator fuses observations from an inertial measurement unit, an optical flow smart camera and a time-of-flight range sensor, Figure 9. The smart camera provides optical flow measurements up to a rate of 200 Hz, avoiding the computational bottleneck to the main processor produced by all image processing requirements. To the best of our knowledge, [8] was the first example of extending the use of these smart cameras from hovering-like motions to odometry estimation, producing estimates that are usable during flight times of several minutes. Figure 10 and 11 show the navigation scheme and an error analysis.

Fig.9. Bottom view of the Hummingbird quadrotor used in the experiments[9]. The vehicle is equipped with a built-in IMU, a smart camera and a time-of-flight range sensor.

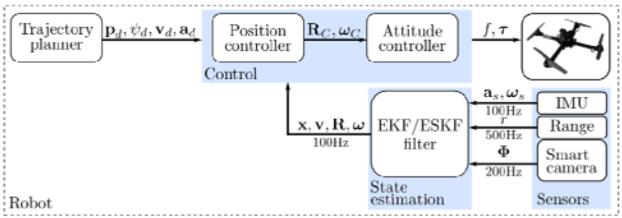

Fig.10. Overview of the architecture pipeline for estimation and control.

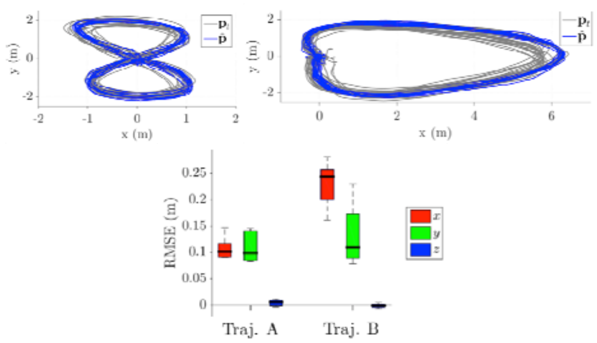

Fig.11. Error analysis of two trajectories with 25 runs each. All runs are executed fully autonomously with a maximum cruise velocity of 1 m/s. Two trajectories are shown in top frames: Trajectory A (left) and B (right) In bottom frame is the RMSE analysis of both trajectories

Perception for robot operation

UPC has been working in the analysis of the support sensors for aerial and ground robot operations. First, different sensors have been considered for robot operation in industrial pipes, and specifically in those situations where the aerial robot has to obtain precise measurements of them meanwhile it is flying. We have analyzed the use of monocular and stereo cameras together with 3D LIDAR measurements, and how this information can be fused to obtain precise estimations robot and object pose estimations. We have also studied which techniques can be used for this operation, and at present some tests have been done using monocular SLAM and line detections from pipes' edges.

Second, we have analyzed which are the sensors required to help the crawler landing operation in the pipe and to grasp it, including different alternatives in reference to the landing operation control: manual, semi-automated or fully automated. In each of these alternatives, we have discussed the sensors and techniques to be used, and how we will integrate the human-in-the-loop.

Finally, we have analyzed how to combine the measurements from crawler sensors when this is performing an inspection task on a pipe, leading to the conclusion that crawler localization estimations are subject to the final prototype sensors' precision. In case of precise measurements, the crawler IMU and wheels' odometry estimations can be combined to obtain the localization of the crawler at low frame rate (between 1Hz and 5Hz), including localization updates from the aerial robot when the crawler operates in its FoV, allowing detections of artificial markers using computer vision techniques.

The combination of the previously mentioned sensors of the aerial and crawler robots are schematized in Figure 12.

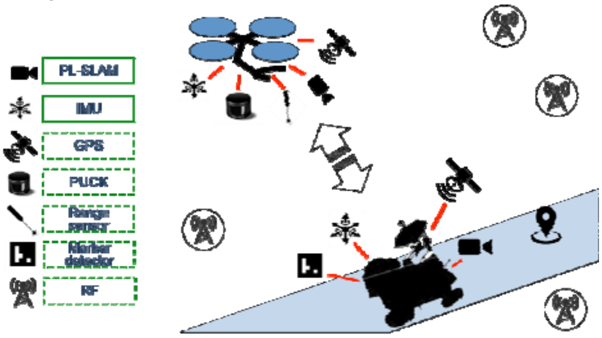

Fig.12. Conceptual scheme of sensors to be used from the aerial and crawler robots for pipe inspection operations.

CONCLUSIONS

In this article a systematic way to build a project for buildings inspection and maintenance has been explained. When unmanned aerial vehicles are used in this kind of applications, some steps have to be followed due the high complexity in giving autonomy to those robots. Teleoperation is only useful at high distances, but when robot approaches to surfaces an automatic navigation scheme has to be used, and this a real challenge. With the use of robotic technology (not only aerial) many solutions can be given to building construction, inspection and maintenance.

Acknowledgments

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