A Vision-Based Guidance System for UAV Navigation and Safe Landing using Natural Landmarks

**A. Cesetti · E. Frontoni · A. Mancini ·
P. Zingaretti · S. Longhi**

Abstract In this paper a vision-based approach for guidance and safe landing of an Unmanned Aerial Vehicle (UAV) is proposed. The UAV is required to navigate from an initial to a final position in a partially known environment. The guidance system allows a remote user to define target areas from a high resolution aerial or satellite image to determine either the waypoints of the navigation trajectory or the landing area. A feature-based image-matching algorithm finds the natural landmarks and gives feedbacks to an onboard, hierarchical, behaviour-based control system for autonomous navigation and landing. Two algorithms for safe landing area detection are also proposed, based on a feature optical flow analysis. The main novelty is in the vision-based architecture, extensively tested on a helicopter, which, in particular, does not require any artificial landmark (e.g., helipad). Results show the appropriateness of the vision-based approach, which is robust to occlusions and light variations.

Keywords Vision · Navigation and control · Autonomous navigation and landing

A. Cesetti (✉) · E. Frontoni · A. Mancini · P. Zingaretti · S. Longhi
Dipartimento di Ingegneria Informatica, Gestionale e dell'Automazione,
Università Politecnica delle Marche, Ancona, Italy
e-mail: cesetti@diiga.univpm.it

E. Frontoni
e-mail: frontoni@diiga.univpm.it

A. Mancini
e-mail: mancini@diiga.univpm.it

P. Zingaretti
e-mail: zinga@diiga.univpm.it

S. Longhi
e-mail: sauro.longhi@univpm.it

1 Introduction

A helicopter is a well-suited air vehicle for a wide variety of operations, ranging from search and rescue (e.g., rescuing stranded individuals or launching life buoys at drowning people) to surveillance and inspection missions (e.g., landmine detection or inspection of towers and transmission lines for corrosion and other defects). All these applications demand dangerous flight patterns in close proximity to the ground or to other objects that can attempt to the pilot safety. Additional hazards derive from operations in dangerous or contaminated areas, e.g., inspection after chemical or nuclear accidents. An unmanned helicopter that operates autonomously or is piloted remotely will eliminate these risks and increase the helicopter's effectiveness. Typical missions of autonomous helicopters require flying at low speeds to follow a path or hovering near an object. Positioning equipments such as Inertial Navigation Systems (INSs) or Global Positioning Systems (GPSs) are well-suited for long range, low precision helicopter flights and fall short for very precise, close proximity flights. Manoeuvring helicopters close to objects requires accurate positioning in relation to the objects. Visual sensing is a rich source of data for this relative feedback.

Unmanned Aerial Vehicles (UAVs) constitute a research field that has been extensively explored in the last decade [1]. In literature a wide range of studies on autonomous helicopters has been reported: modelling and identification, simulation, sensor integration, control design and fault diagnosis [2–5].

The use of computer vision as secondary or primary method for autonomous helicopter control has been discussed frequently in recent years, since classical combination of GPS and INS systems can not sustain autonomous flight in any situation [6, 7]. Several studies have demonstrated the effectiveness of approaches based on motion field estimation [8] and feature tracking [9] for visual odometry.

A global view of the main aspects related to the research field of computer vision for UAVs can be found in [10], along with the results of applying these techniques in several applications. In [11] Caballero et al. propose a work on visual odometry based on geometric homography. They use vision to compute a frame by frame odometry for Simultaneous Localization And Mapping (SLAM). A cooperative vision-based system for detecting and tracking objects of interest on or near the ground is presented in [12].

Vision based methods have been proposed even in the context of autonomous landing management: in [13] Merz et al. utilize inertial sensors combined with a single camera and a specially designed landing pad in order to be independent from GPS; in [14] Daquan and Hongyue estimate all the motion parameters of the aircraft are obtained by exploiting images of an airport runway lighting acquired by the airborne camera. The problem of how to land a helicopter in unknown terrain is tackled in [15]. A combination of feature tracking, motion estimation, and multi-frame planar-parallax obtained by a stereo rig is utilized in order to estimate a digital elevation map of the terrain, allowing the determination of a safe landing area of terrain and map waypoints to a desired landing spot.

In general, we can say that the degree of autonomy that an helicopter can achieve depends on factors such as the ability to solve unexpected critical situations, e.g., loss of GPS signal, and the ability to interact with the environment, e.g., using natural landmarks. A vision-based solution for autonomous waypoint navigation and safe

landing on unstructured terrain represents a strong improvement for both these abilities. Several techniques have been implemented, decoupling the problem of locating and tracking a high contrasted, well known landmark, e.g., a classical helipad that can be easily identified by standard image processing techniques [16–18], from the problem of detecting and avoiding natural obstacles, e.g., steep slopes and rocks on a landing area [19–21]. The dependence on fixed, artificial landmarks and on optimal visibility conditions constitutes a strong limit for visual-based navigation in real-environment applications. In some works vision approaches based on moment descriptors are used; they impose no constraints on the design of the landing pad except that it should lie on a two dimensional plane, but artificial landmarks composed by polygons are indispensable [17]. Moreover the weakness of that strategy appears in situations in which natural (e.g., due to debris or leaves) or artificial (e.g., due to engine smoke) occlusions can make the computation of moment descriptors very difficult.

In this paper a vision based approach for guidance and landing of an UAV is proposed. Differently from previous works in this field this paper presents a vision-based system for guidance and safe autonomous landing of a helicopter based on the concept of reuse of local features extracted from the vision system. The vision based architecture, better described in Section 3, is novel and even if presented here in the case of helicopter navigation and landing, can be applied to any UAV, even fixed wing vehicles. The general idea is to guide the UAV using natural landmarks only, which can be selected from aerial images of the operating area. Such images can be already available before or just acquired during the flight. The features extracted from the natural landmarks can be chosen as navigation targets allowing a vision-based feature tracker to compute the references for the flight control.

The main aim of such approach is to provide a remote operator with an intuitive and direct control system, exploiting the benefits deriving from the use of visual information, which constitutes the friendliest interface for an operator to interact with the environment. Through the video stream the operator is able not only to supervise but even to directly lead the operations, assigning the desired navigation targets. Manoeuvres are then managed by the on board control system.

The main advantage of this approach consists in computing the displacement relatively to the target rather than through a coordinate system fixed to the earth. This approach becomes particularly useful in all those situations in which GPS signal is not available (e.g., when operating in urban like environments or in case of fault) or target coordinates are unknown. Moving the UAV using the visual feedback that the operator receives from the on-board camera can be really useful when the path can not be planned before, as during search and rescue or investigation missions.

In the case of landing on unstructured areas the ground is analyzed to verify if the area is flat and proper for landing, since Digital Elevation Map (DEM) resolution can not guarantee the possibility to identify a flat and safe target area. The landing task is managed by the vision system through the localization of the geometrical centre of mass of the matched features. Appropriate feedbacks are given to the autonomous landing control system.

In this paper studies have focused on the problem of natural landmark detection and recognition and safe landing area detection, which, as said before, are the main novelties of the paper; for this reason we focused results on the vision based methods,

leaving a minor space to the validation of the control system. Results show the appropriateness of the vision based approach, which is also robust to occlusions, light variations and scene changes (i.e., reference images grabbed in different days and hours).

The organization of the paper is as follows. In Section 2 the problem of locating, tracking and inspecting an assigned landing area is formulated. In Section 3 the vision approach, a feature-based image-matching algorithm, is presented. Section 4 describes the hierarchical behaviour-based control architecture. Section 5 presents the results achieved. Finally in Section 6 concluding remarks and directions for future improvements are discussed.

## 2 Test-bed and Experimental Task

The experimental test-bed HELIBOT is a customized Bergen Twin Observer. It is a twin-cylinder, gasoline-powered radio-controlled model helicopter approximately 1,5 meters in length and capable of lifting approximately 9 kg of payload. Onboard avionics include a PC/104-based computer stack running the QNX RTOS (800 MHz PIII CPU with 256 MB DRAM and 256 MB flash disk), a GPS-41EBF3V receiver with WAAS and EGNOS (available in Europe) corrections and a Microstrain 3DM-GX1 Attitude Heading Reference System (AHRS). The helicopter is also equipped with a downward-pointing Nikon camera. The ground station is mainly constituted by a laptop, used to send high level control commands to the helicopter as well as displaying telemetry from it. Data are sent using an advanced radio modem that transmits and receives on the 868 MHz band. Autonomous flight is achieved using the hierarchical behaviour-based control architecture presented in Section 4.

The testing of algorithms was largely performed using a simulation framework developed by our research group. The framework is provided with a customizable HELIBOT model, allowing an easy switching from simulated to real tasks.

As shown in Fig. 1 four operating modes are proposed for the high level control system. The approach to the operating area is managed with the aid of GPS information. The user gives to the system the waypoint coordinates and the helicopter is autonomously guided to the goal. Then the operating mode is switched and vision system enters into the control loop. The user analyzes a high resolution image of the area and selects a target. The system extracts the appropriate features from the target image to define a natural landmark and starts to search it in the image sequence coming from the onboard camera. Once features are detected and tracked, the system uses the image location of these features to generate image-based velocity references to the low level attitude and height controllers.

In the case of a programmed landing, the vision-based controller pilots the helicopter over the landing area and manages the landing. If the landing area is unknown, an appropriate analysis is performed to select the nearest flat area for a safe landing.

Figure 2 shows the flying area in which experimental tests have been carried out. The vision algorithm is described in the next session.
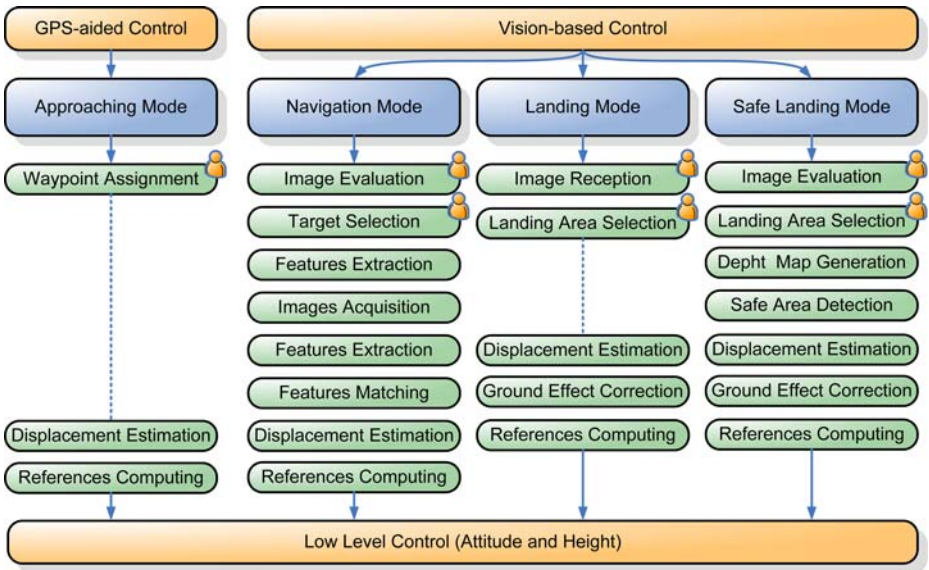
Fig. 1 Control system operating modes

3 Vision Based Approach

The main difficulty to attain fully autonomous robot navigation outdoors is the fast detection of reliable visual references, and their subsequent characterization as landmarks for immediate and unambiguous recognition. The vision approach presented here following is based on the concept of natural landmark. This system allows a user to control the robot choosing the navigation target in the images received from an on-board camera or from a high resolution aerial or satellite image. This form of navigation control is convenient for exploration purposes or when there

Fig. 2 The "Gruppo Aeromodellistico Rio Ete" flying area

is no previous map or knowledge of the environment, situations in which systems like GPS, even if available, become useless and can be discarded. The user can decide the next target for the robot and change it as new views of the environment become available. This vision based navigation approach was also used to locate a landing area and to allow autonomous landing by giving feedbacks to the UAV control system.

Figure 3 depicts this concept, underlining the key idea that any high level task relies on the same features extracted at the lower layer. This ensures time performances of the whole approach and the chance of choosing different feature extractors, following research developments in computer vision, but not depending on a single approach.

The vision based system performs also a scene analysis to obtain a first rough classification of the safe landing area. All elaborations are based on the same feature set extracted from the current image and elaborated for different purposes: navigation, waypoint identification, landing area detection, safe landing area classification. Processing is based on high level analysis of point features, which in this approach are extracted using SIFT [22], but that could be extracted using any feature extraction algorithm able to detect stable points and to provide a robust descriptor.

3.1 Feature Detection for Natural Landmark Tracking

The system should be able to detect natural landmarks in unstructured outdoor environments while the robot is operating. These natural landmarks must provide reliable matching results. To overcome the inherent difficulties with matching images of an object or a scene captured outdoor during motion, the description of landmarks must be based on invariant image features. These features must be distinctive and invariant or partially invariant to translation, rotation, scale, 3D camera view point and outdoor illumination conditions. Furthermore, robustness to image noise, occlusion, background changes and clutter should be granted while maintaining near real-time feature extraction and matching performance.

To solve all the discussed aspects an improved version of the Scale Invariant Feature Transform (SIFT), developed by Lowe [22, 23] is used. SIFT is invariant
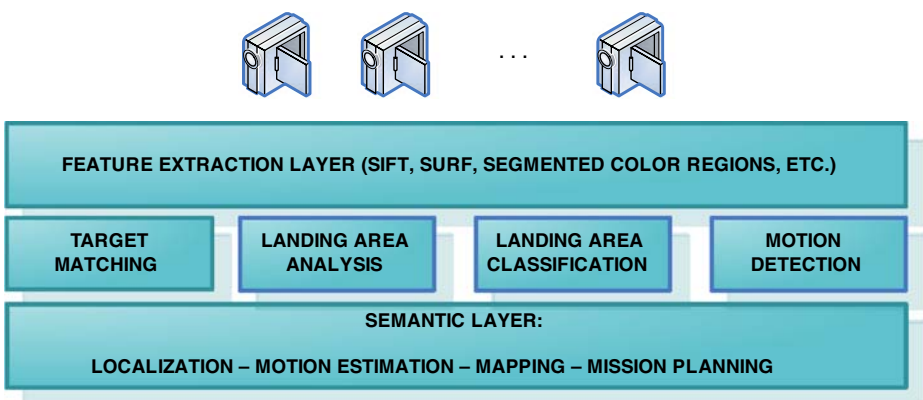
Fig. 3 The vision based architecture

to image translation, scaling and rotation. SIFT features are also partially invariant to illumination changes and affine 3D projection. These features have been widely used in the robot localization field as well as many other computer vision fields. SIFT features are distinctive and invariant features used to robustly describe and match digital image content between different views of a scene. While invariant to scale and rotation, and robust to other image transforms, the SIFT feature description of an image is typically large and slow to compute. Our improvements, better described in [24, 25] consist of two different steps:

1. Divide the image in different sub-images;
2. Adapt SIFT parameters to each sub image and compute SIFT feature extraction, only if it is useful.

During the first step, the image is divided into several sub images according to its resolution. The number of scales to be computed is also decided. The image is doubled at the first step of the SIFT algorithm. During the second step the following threshold value (Tr) is computed to define the contrast threshold value of the SIFT algorithm.

$$Tr = k \cdot \frac{\sum_{i,j=0}^{DimX, DimY} \left| I\left(x_i, y_j\right) - \overline{I}\left(x_i, y_j\right) \right|}{DimX \cdot DimY}$$

In the previous expression k is a scale factor, $DimX$ and $DimY$ are the x and y image dimensions, $I(x,y)$ is the intensity of the gray level image and $\overline{I}(x, y)$ is the medium intensity value of the processed image. In the Lowe's SIFT implementation the contrast threshold is statically defined and low contrast key points are rejected because they are sensitive to noise. To speed up the feature extraction every sub-image that has a very low threshold value is not computed because of the high probability of not finding features in an almost constant image region (i.e., extreme detection algorithm will fail). Further details of the used approach can be found in [24, 25].

This method is also known to be robust to partial occlusions, such as those caused by engine smoke (Fig. 4) and can obtain time performances comparable with other fast feature extractors; in particular our experiments demonstrated that the system was able to elaborate five frames per second using a 320×240 pixel image series.

The matching of a natural landmark in an image is then refined using the computation of the centre of mass C of a subset of matched features; relying on the assumption that a single landmark is present in each image, we analyze the group of features by calculating the cluster that minimizes the relative distance of the 80% of the total number of features.

This ensure that isolated false matches, usually far from the landmark centre, are deleted in the computation of C, whose coordinates (x_c, y_c) are finally used as feedback for the landing control system.

The metric used to compare feature descriptors is a classic Euclidean distance and some heuristics (i.e., discard frames with only few features extracted, etc.).

At the present state of our research we do not perform a real feature tracking, but we simply evaluate feature matching between every frame and the set of way points or landing areas. Here following we often name this methodology landmark detection and tracking.

Fig. 4 Typical occlusions caused by engine smoke; camera is mounted on the bottom of the UAV and it points the terrain

3.2 Optical Flow for Safe Landing Area Classification

Surface reconstruction can be defined as the process of inferring a mesh of interconnected points representing a three-dimensional surface. The surface is often assumed to be rigid and fixed. Computer vision systems ideally would like to be able to reconstruct objects or environments from a sequence of pictures.

In the UAV application presented in this paper we are interested only in depth estimation to determine if the landing area is safe for landing.

To reach this purpose we use two different approaches, based on typical helicopter movements. The first case assumes that images are taken at a constant height and with a pure translational motion; this restriction can be overcome since the control system can assure those flight conditions during landing area inspection. The second approach assumes that the helicopter is approaching the landing phase and is moving maintaining the position and decreasing the altitude to complete a pure vertical landing; also in this case we use the feature-based vision system to inspect the landing area relying on the same set of local features. This motion is quite typical too and can be easily managed by the control system.

In the first case we use an optical flow for depth perception that allows safe autonomous landing. The system is based on feature-based surface reconstruction using an optical flow computation. This approach chooses image features that are stable for large motions. Thus, a sparse set of very confident depth estimates is obtained. If the surface is considered quite stable the area is used for the autonomous landing maneuver.

First, an image sequence of the target landing area is taken by the camera mounted on the UAV and the SIFT features are used to estimate the optical flow in two successive frames; then, structure (in particular depth) information of target landing area relative to UAV is recovered; finally, a simple classifier based on a binary threshold is used to decide if the surface has variable depth or not and, consequently, if it can be used as a landing area.

Experiments using both computer simulated images and real video images demonstrate the correctness and effectiveness of our method. In detail, the optical flow vector field is evaluated using a simplified approach: the optical flow is computed on the base of SIFT features that have been matched in two consecutive frames captured

by the UAV during a translational flight over the area. Translational optical flow is then filtered on the base of the flow vector orientation and, finally, a computation of the variance of the optical flow module is performed to measure surface flatness. A binary threshold is used to define if the surface is suitable or not for safe landing of the UAV. The threshold adopted is now experimentally determined. A specific study is planned to relate it to some parameters to obtain a dynamic estimation.

Feature extraction and matching algorithms as SIFT are useful to estimate the flatness of a surface especially in translation conditions as above introduced. If $F_k = \{(x_i, y_i, \hat{x}_i, \hat{y}_i)\}, i = 1, \ldots, N_k$ is the set of N_k features at step k formed by quadruples of matched features, we estimate the flatness of surface applying a simple assumption.

Assumption 1 If a vehicle is moving with pure translational motion, the flatness of beneath surface is calculated by comparing the variance of distances between two or more sets of matched features; low variance corresponds to safe areas, while great variations are typical of unsafe regions.

We define $d_k^i = \left\| (x_i, y_i) - (\hat{x}_i, \hat{y}_i) \right\|_j$ as the distance (norm j, with $j = 2$) between two matched features at step k; the flatness of "surface" is calculated as:

$$flatness_k = std\left(\sum_{n=1}^{N_k} d_k^n \right)$$

where *std* is the standard deviation operator applied to a set of data. The classifier is a binary threshold on the *flatness$_k$* value, which operates in the following way:

$$flatness_k = \begin{cases} safe \ if \ < T \\ unsafe \ if \ \geq T \end{cases}$$

The T threshold is calculated by a supervised training phase, where a human operator classifies a set of well known images as *safe* or *unsafe*; this procedure is simple and requires a little spent of time. Other approaches under development focus on a different calculation of T using fuzzy classifiers, which allows to represent the uncertainty; T can be also time-varying, adapting to the number and quality of features extracted.

Some considerations are suitable for clarity. The use of SIFT features is a reasonable proposal since they have been previously extracted and used also for matching. No additional computational load is required. A restrictive hypothesis assumed in the proposed approach concerns the necessity of images taken at a constant height and with a pure translational motion, but this restriction can be overcome since the control system can assure those flight conditions during landing area inspection. The threshold used for classification is now experimentally determined. A specific study is planned to relate it to some parameters in order to obtain a dynamic estimation.

In the second case (vertical landing) we compute a graph of distances between every feature couple and compare, frame by frame, the variation of this array of distances, trying to evaluate the presence of a constant increase of variation, stable over the entire image. This computation is based on the hypothesis that geometric linear zooming over a flat surface brings to constant distance variations. For this

reason we compute the variance of the variation vector as a measure of the previous explained heuristic. High variances bring to the classification of unsafe areas, while very low variance gives us a feedback of the flatness of the landing area. From another point of view this method evaluates a kind of radial movement of features while the helicopter is landing vertically; it is the same case of a zoom aligned with the centre of the image that enlarges every object in the figure. This heuristic evaluator is very quick, even if not exact, due to the possible presence of false feature matches.

An assumption also made in this heuristic surface classification method is the fact that a quite large number of features is extracted almost uniformly from the current helicopter view; the assumption is not restrictive in any of the feature extraction methods here proposed because, usually, they are able to extract hundreds of features.

Here following a short meta code description of the approach is proposed.

3.2.1 Slope Detection Algorithm

– search for feature matchings in a pair of consecutive images;
– calculation of distances among features in the first image (D1 matrix);
– calculation of distances among features in the second image (D2 matrix);
– detection of wrong matchings (if $d1_{i,j} > d2_{i,j}$);
– filtering of inconsistent data;
– calculation of normalized variations in distances among features;
– calculation of mean and the variance of the previous results.

The two methods bring to a correct and conservative classification of the area, choosing only flat surfaces as safe areas. Results, even if preliminary, show the feasibility of the proposed method. Time performances of the algorithm are good because it does not add time consuming evaluations to the feature extraction process.

4 Control Strategy

Unmanned Aerial Vehicles, in particular helicopters as HELIBOT, are complex flying machines. The mathematical model of a reduced scale helicopter has been deeply studied during last years [26]; the various proposed approaches require a large set of well-known parameters (e.g., geometrical, aerodynamic, mechanical) that in the real case are estimated or measured [27]. Simulation environments are useful tools that support the design process of control laws and task management [27]. Given an accurate model of system, simulations assure to save time and money, due to the high costs of UAVs. The introduction of a vision sensor that aids the autonomous navigation and landing requires the development of a hierarchical control architecture. The use of a hierarchical control structure is a widely adopted approach in UAV [28–30], that allows to de-couple the two main aspects:

– High-level control, represented by strategy and task management,
– Low-level control, which translates the assigned behaviour to actuator controllers.

Each level is supported by a set of sensors and/or actuators. In Fig. 5 a graphical representation of hierarchical structure implemented in HELIBOT is shown. The
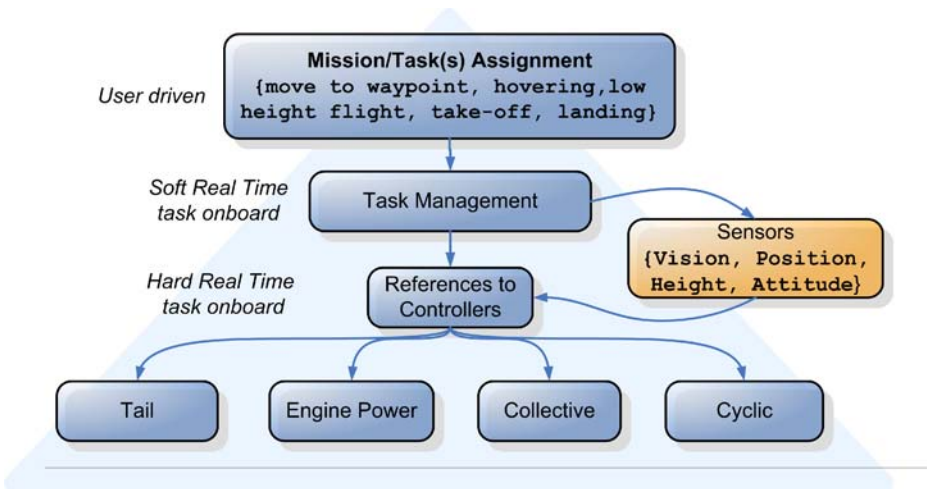
Fig. 5 The hierarchical structure allows to de-couple problems, solved at different level by specialized modules

vision sensor is used to track features of interest in the field of view. For improving the robustness to loss/degradation of GPS signal, information retrieved by the computer vision algorithms is fused with position data obtained by GPS (with EGNOS corrections) and inertial data by AHRS.

The top level is represented by Mission/Task(s) Assignment module, where the interaction between UAV and human operator is maximum. Task management is a part of Flight Management System (FMS) [27] and generates the path to accomplish a specific task. The last level manages the control of actuators. The complexity of mathematical model of helicopter justifies the use of model-free controllers. A triple nested PID control scheme has been implemented for HELIBOT as shown in Fig. 6.

As stated in the previous section, where the vision-based approach has been presented, to locate the landing area or to explore a zero-knowledge area, common approaches can fail due to non-robust techniques (e.g., scale, rotation, change of light conditions, point of view). The use of landmarks, natural or artificial, gives the Task
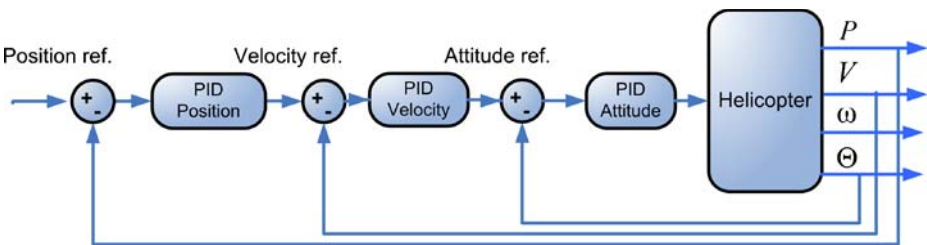
Fig. 6 The nested PID controllers scheme separates the problem of minimizing position error assuring moderate speed when error is high and low speed when the error tends to be small

Management module the capability to control the vehicle even in presence of faults, such as loss/degradation of GPS signal. The question is when and how to switch from the standard behaviour, basically driven by standard sensors, to the vision aided behaviour. The challenge is to ensure the stability during the switching. Simulation stages are useful to predict the dynamics of helicopter during the switch.

4.1 Switching Control Strategy by Behaviour

Switching control is a common approach when one controller is not sufficient to cover the dynamics of a plant/process. A set of controllers tuned on a particular operational condition often guarantees better performance in terms of precision to external references and robustness to change of parameters. In the considered case, the switch occurs when there is a change of task. Standard controllers used for navigation are not suitable for fine tuning, as required in the landing task. In fact, during navigation high accuracy and precision in terms of position, velocity and attitude are not required, while in a critical task as landing a high accuracy on position is required and the use of dedicated sensors as vision systems and range finders (e.g., laser or sonar) becomes necessary.

In Fig. 7 the proposed switching architecture for attitude is shown. The structure of the tail controller and the engine power is similar, but is not reported here for the sake of brevity. The main difference from the control scheme of Fig. 6 is the introduction of a supervisor and a vision based controller. The supervisor acts switching the controller, taking into account that a switching condition must be satisfied to avoid the loss of stability. References from the vision based controller are imposed without velocity loop because the speed in this phase is low.

Switching Condition   A switching at time k can occur if and only if speed (translational and angular) tends to zero.

The condition is a bit conservative, but it is reasonable in the context of landing or low speed feature tracking. The advantage of low speed during transition is the reduced magnitude of bump between old references and new ones. The vision based
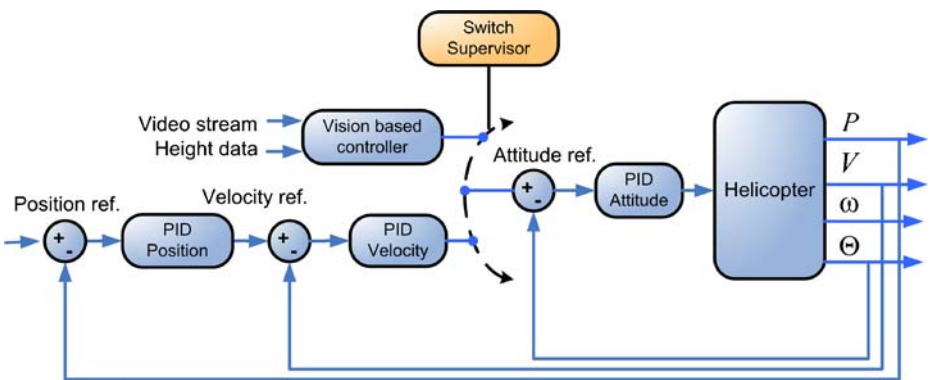
Fig. 7 Switching architecture for fine tuning tasks as landing or low speed features tracking

controller provides fine planar alignment between helicopter and features found in the landing area and height over ground is also regulated. The vision based controller acts as a quasi-proportional controller, as shown in Fig. 8, where a dead zone is introduced to overcome chattering problems induced by small oscillations around the equilibrium. Saturator levels, both for maximum and minimum changes, avoid to impose dangerous references (e.g., high values in collective can cause the overturn of helicopter).

An integral action with saturation can be added to increase the steady state precision in terms of position error. A more complex scheme that makes use of fuzzy rules is under development.

4.2 Ground Effect Estimation during Low Height Flights and Landing Flights

Ground effect is an aerodynamical effect that turns significant when the helicopter flights at altitudes that are comparable with the main rotor span. The main effects related to this phenomenon are a significant increase of lift and a reduction of induced velocity. The problem is well known and deeply investigated especially after First World War, when the military forces understood the tactical importance of helicopters due to the hovering feature of these vehicles.

During the last period many approaches have been proposed to precisely model the unsteady aerodynamics of rotorcraft In Ground Effect (IGE). Several dependences (e.g., blade loading, blade aspect ratio, twist) are weak and not significant for control purposes. Well-known simple models bind the rotor span normalized altitude (height / rotor span) with an increase of thrust or, alternatively, a reduction of induced velocity. In Fig. 9 the behaviour of T/T_{inf} ratio is reported, where T_{inf} is the thrust out of the ground effect.

Taking into account the ground effect, the altitude controller is improved introducing the dynamics of thrust when the helicopter is approaching to ground. Following the control scheme previously introduced (Fig. 6), two controllers must be revised: the collective controller and the engine gas controller. They are responsible of varying the helicopter altitude when the attitude is proximal to zero. The gas controller tends to maintain the same main rotor speed Ω_{MR} and the collective controller is varied to control the thrust. In the case of IGE, a gain scheduling

Fig. 8 Transfer function between input from vision algorithms (difference Δx in position along an axis between helicopter and target) and variation Δu of attitude reference
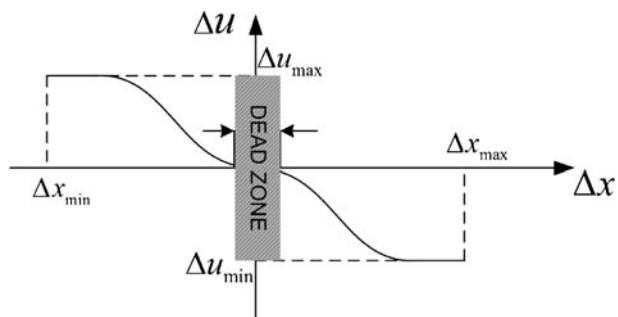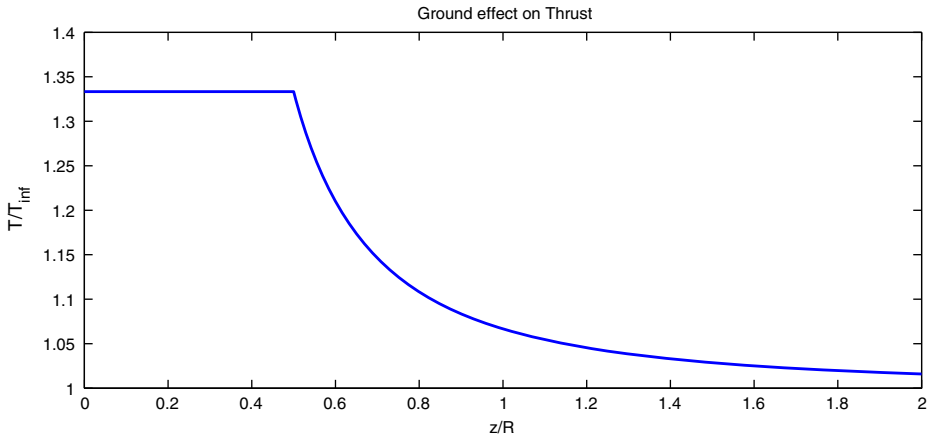
Fig. 9 The considered ground effect on thrust

approach is used to tune in real time the controller gain. In this condition Ω_{MR} is lightly reduced owing to the increase of lift. Gain is expressed by:

$$\hat{K} = K\,(\alpha k_G) \quad 0 \leq \alpha \leq 1$$

where K is the nominal gain value in the case of Out of Ground Effect (OGE), α a weighting factor and k_G is related to the variation of lift, calculated at each step by the following formula:

$$k_G = \frac{1}{0.9926 + 0.03794\left(\frac{2R}{z}\right)^2}$$

A graphical representation of gain scheduling approach in Fig. 10 is shown. Gain scheduling can be applied to both collective and gas controllers.
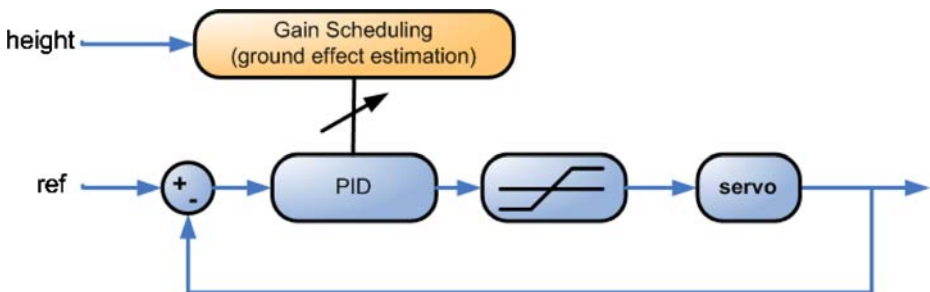
Fig. 10 Gain scheduling applied to PID that controls the collective to contrast the ground effect

5 Experimental Tests

This section is organized as follows: first, results about simulations of the control system using the visual feedback as input in a virtual scenario are presented. Then, simulation results of ground effect during low height flights and landing flights are described. Finally, the visual feedback is evaluated using a real scenario and presenting results about the navigation and landing, taking into account also the safe landing area detection.

5.1 Simulation of Vision Sensor Feedback in a Virtual Scenario

As mentioned above, simulation is needed to evaluate the behaviour of the helicopter in transition stages. All the simulations have been carried out on a complete MATLAB/Simulink model. The virtual scenario shown in Fig. 11, developed in VRML, allows to increase the reality of simulation.

In this case, it is possible to simulate dynamically a vision sensor exploiting the camera property of VRML. More complex scenarios with real textures can be also used to stress the system more. All other sensors as GPS and AHRS are integrated in the developed simulator, allowing a full test of the system. Vision algorithms, based on feature extractors and matching, run synchronously with the simulation of helicopter's dynamics.
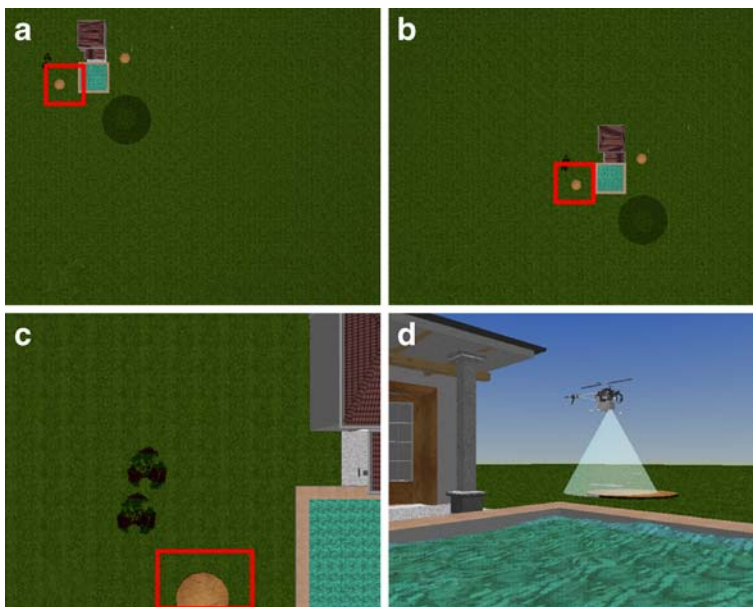
Fig. 11 **a** the initial frame when the vision system detects features of interest as helipad or other known structures; **b** tracking is active and the helicopter performs fine tuning to reach the target; **c** the helicopter attempts to reduce height over ground; **d** simulated scenario in VRML
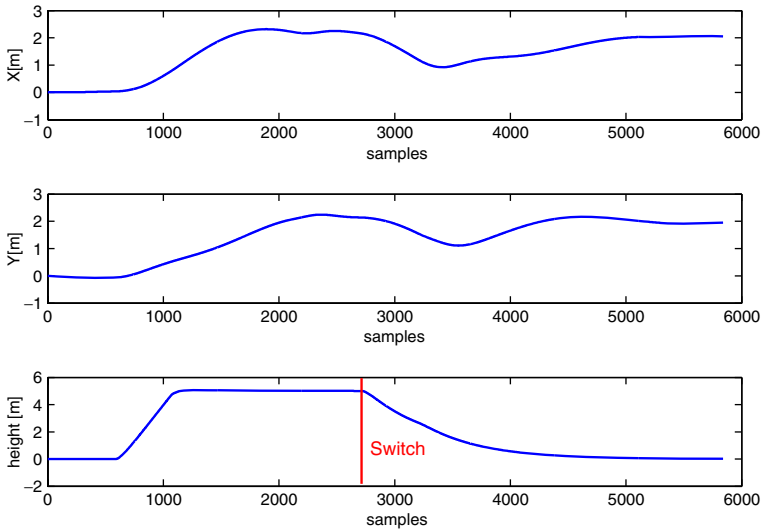
Fig. 12 Graphical representation of position along x,y,z axes

In Figs. 12 and 13 the results of a simulation in the developed multi-agent simu-
lator are shown. The simulation shows a switch from normal behaviour (waypoint
following) to landing in a safe area detected by the vision algorithm.

Switching is not critical because the relevant change involves the heading of the
helicopter as shown in Fig. 13; a low speed transition, which guarantees stability, is
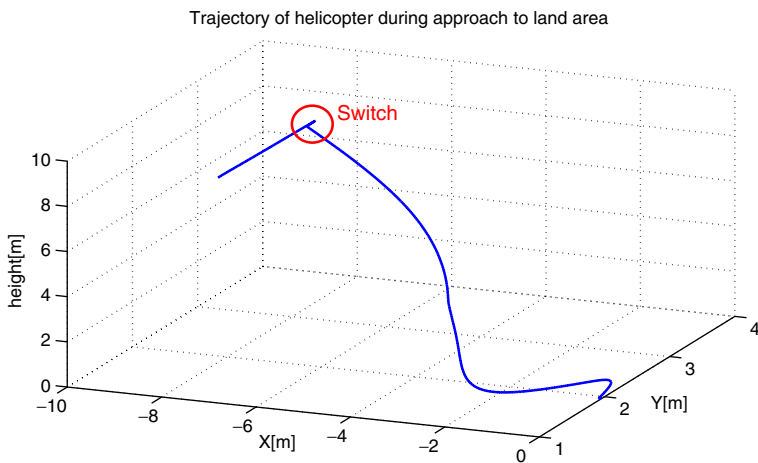
Fig. 13 3D graph of trajectory followed by the helicopter during the mission; the switch introduces
a singularity only in the change of orientation along the yaw axis, which does not imply a loss of
stability

maintained as required. Switch is triggered by the vision controller that detects the landing area; this high level information is then used by the supervisor, which takes the decision to switch from standard to vision-based control.

5.2 Simulation of Ground Effect during Low Height Flights and Landing Flights

In Figs. 14, 15 and 16 results for an interesting scenario are presented. The scenario is characterized by the presence of a switch that simulates a trigger from the vision sensor system to start an emergency/urgent landing in a safe area. Then the helicopter quickly reduces the altitude and receives the command to flight at very low altitude (0.25 m) to test the performance of the controller during the IGE hovering.

The helicopter switches from standard navigation (as shown with red line in Fig. 16) to landing task; in the last phases the rate of descent is low according to desired behaviour. Ground flights are suitable for special tasks as mine detection, where the helicopter is equipped with a Synthetic Aperture RADAR (SAR); in
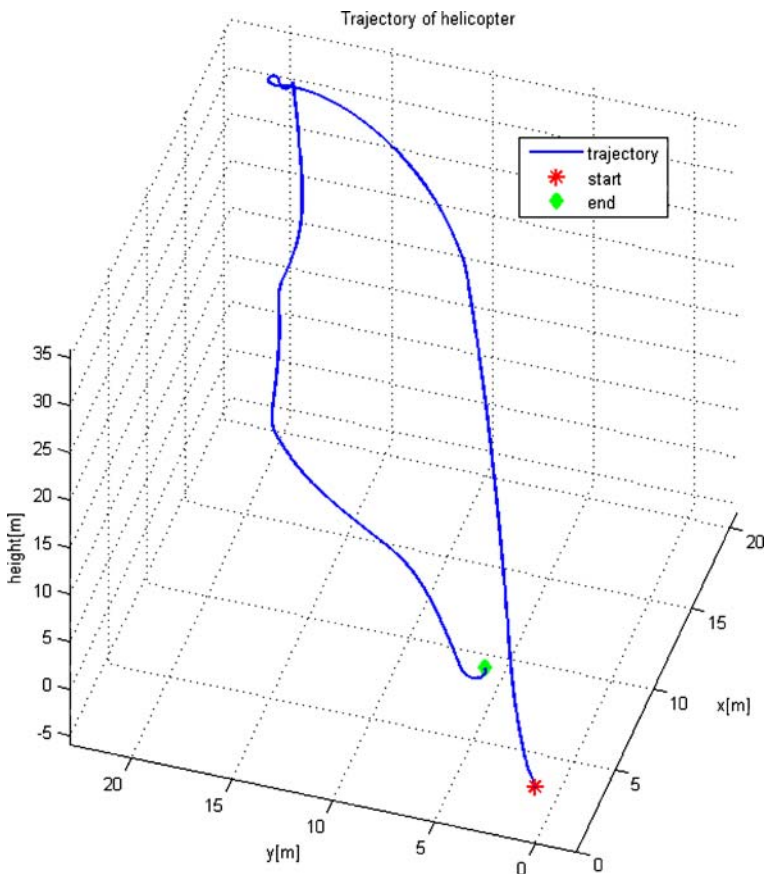
Fig. 14 Trajectory of helicopter during entire mission
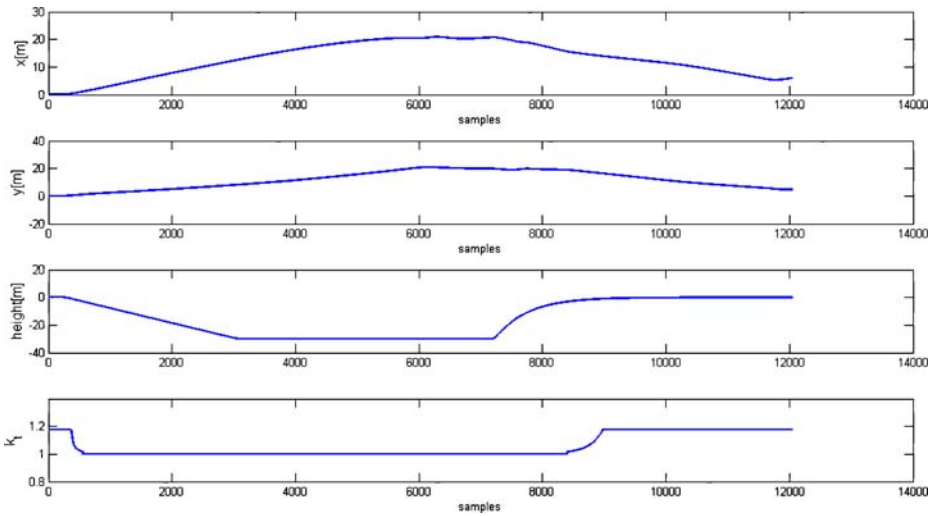
Fig. 15 Diagram of positions (*horizontals* and *vertical*); *bottom graph* reports the trend of corrective factor to contrast the ground effect

this case it is essential that the distance (also speed) between antenna and ground is minimal.

5.3 Vision Results in Real Scenario

For the vision part, images with 320×240 pixels and shot by a Nikon camera are used. These images can be processed at five frames per second. In the case of autonomous landing this is also the frequency of the feedback input to the control system. The vision system has been tested in different situations: the tracking of a natural landmark for waypoint based navigation, the landing using a natural landmark and giving a feedback to the control system, the detection of a safe landing area.

Figures 17 and 18 show the matching between the frames while the UAV is flying over natural landmarks. This test was performed to show the robustness of the vision system when the UAV is far from the landmark and is moving at high speed. Blue lines are the results of the feature matching used to track the waypoints. In Fig. 17 is also visible the smoke produced by the engine of the UAV, which causes several partial occlusions; the system behaves well also in these cases, due to the high number of features being tracked. In Fig. 19 an example to show the rotational invariance of SIFT matching is presented.

The next test shows the feasibility of the feature tracking system to guide an autonomous vision based landing. Data collected from this test are also used for a simulation of the safety analysis of the landing area, at the end of this section. The altitude feedback is given to the control system evaluating the centre of mass of matched features with respect to the centre of the actual view. Figure 20 shows a sequence of a landing using always the same feature-based approach and a natural landmark.
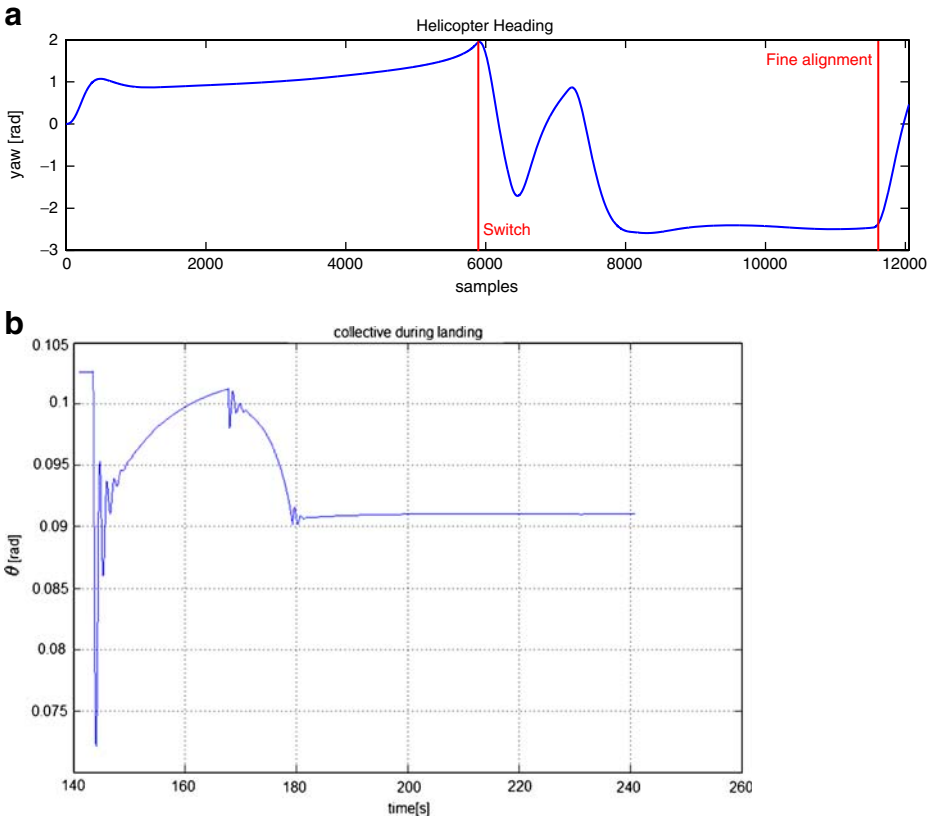
Fig. 16 Heading of helicopter during mission; red lines evidence significant instants (switch and fine alignment)

The final tests were performed to evaluate the optical flow approach for a safe landing area classification system on the real UAV. Firstly, images taken during linear flights at constant height over the ground (first case described in Section 3)
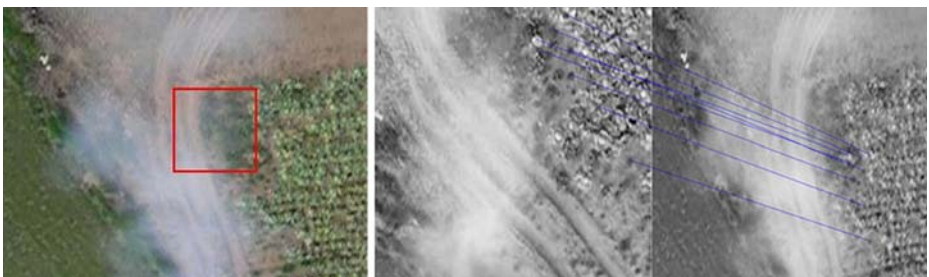

Fig. 17 Tracking of the landing area with respect to the given one, using a natural landmark and dealing with smoke occlusions
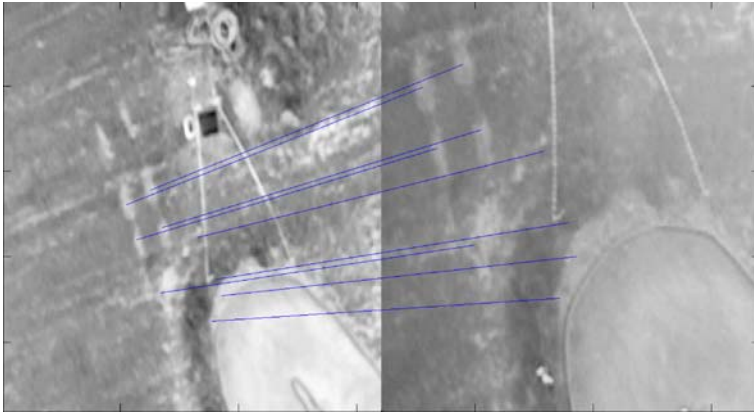
Fig. 18 Matching between two frames using a natural landmark for landmark localization and tracking

have been analyzed. Here following two different cases of depth estimation and surface classification are reported. In Fig. 21 two illustrative sequences of images taken flying over an unsafe area (Fig. 21a) and a safe (Fig. 21b) area are shown. Every pair of consequential images was analyzed. A variance analysis of geometrical characteristics of the blue lines obtained from SIFT feature matching was performed and a representative value computed. Figure 22 shows two different situations: the first matching (unsafe area) presents a variance parameter almost hundred times greater than second one (safe area). The variance parameters in Fig. 22a and b are 382.06 and 2.78 respectively, with an experimentally determined threshold of 50.

A second test (case of vertical landing described in Section 3) was also performed in a real scenario. The radial movement of features, shown in Fig. 23, is the base of the heuristic that evaluates the kind of surface and, according to an experimental
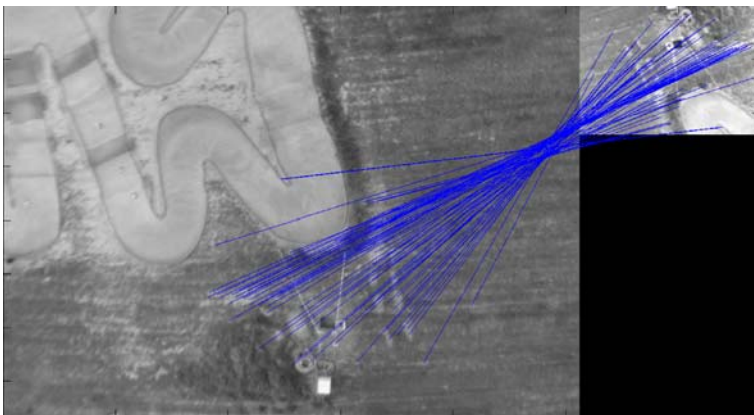
Fig. 19 An example to show the rotational invariant SIFT matching
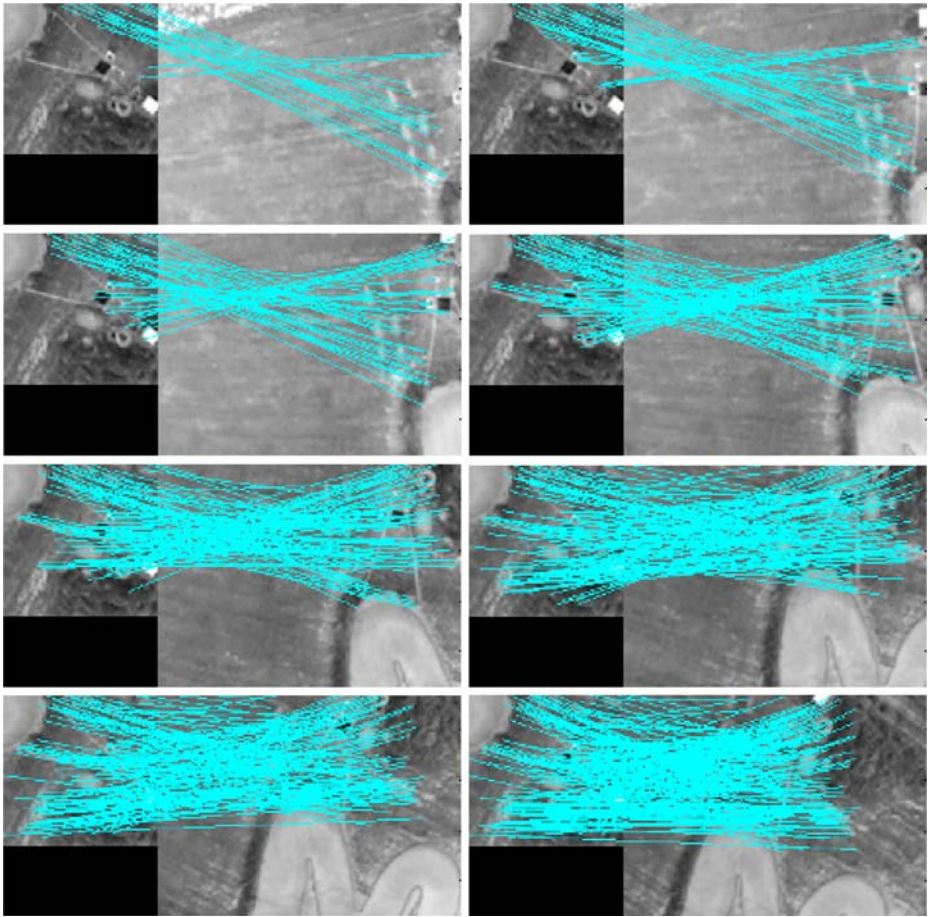
Fig. 20 A sequence of target identification and tracking used for autonomous navigation and landing

threshold, classifies the safe landing area. Figure 23 shows the case of the helicopter approaching a safe (Fig. 23a) and an unsafe (Fig. 23b) landing area. In the first case the control system allows the helicopter to land. In the second case the safe landing area classification gives back to the supervisor the command to leave the area because it is unsafe.

Figure 24 is the comparison between parameters of the safe and unsafe area. The evaluation of the variance of the distances between features among all extracted features and frame by frame during the vertical landing, is a good and fast methodology. The heuristic does not add computational time to the process with respect to the feature extraction process, which is much bigger than all the post processing here proposed and presented. This enforces the general idea of re-using the same features extracted for landing area detection and tracking for other purposes, such as the safe landing area classification.

Other preliminary results were obtained using SURF and other variants of these approaches, previously cited. All bring to very similar results and here only SIFT

a

b

Fig. 21 Two illustrative sequences of images taken flying over an unsafe area (**a**) and a safe area (**b**), respectively

ones are presented. The proposed approach is totally general and applicable to any kind of local feature extractor.

The real scenario results obtained with the use of HELIBOT are encouraging and current works are on the extension of this approach for motion analysis of the landing area (e.g., avoiding streets or flat areas used by people).
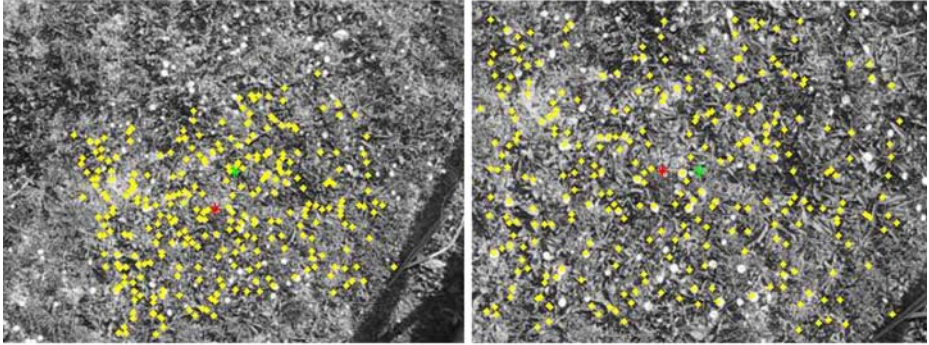
6 Conclusions and Future Works

In this paper the design and implementation of a vision-based landing and navigation algorithm for an autonomous helicopter has been presented. A hierarchical behaviour-based controller exploits alternately GPS and vision input data, allowing the helicopter to navigate from an initial position to a final position in a partially known environment, to locate a landing target and to land on it. The vision system
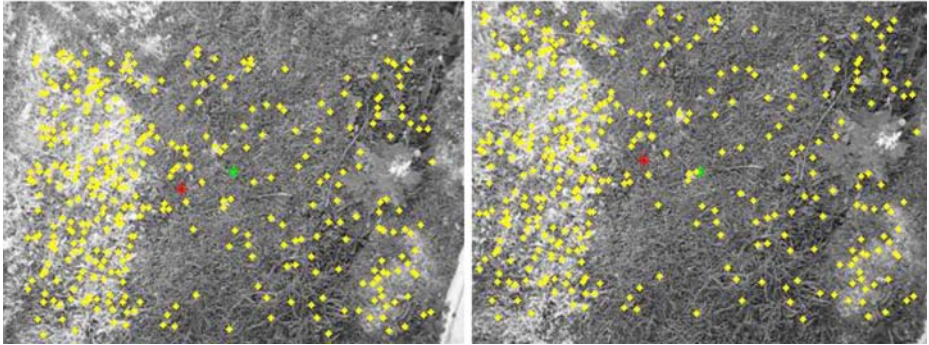
a   **b**
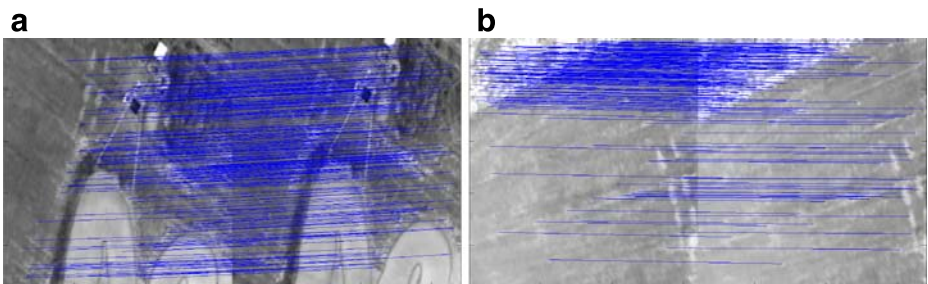
Fig. 22 SIFT Features matching analysis. Variance parameters are 382.06 (**a**) and 2.78 (**b**)
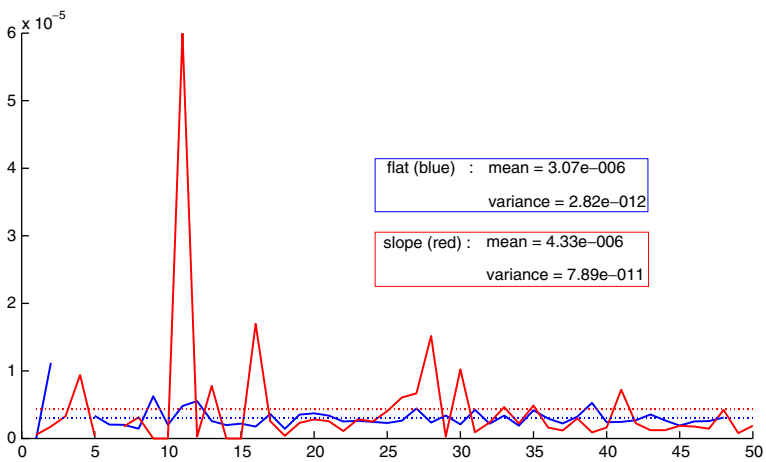
Fig. 23 Frame by frame matching of a safe (**a**) area and of an unsafe landing region (**b**). Evaluated parameters are reported in next figure

Fig. 24 Mean (*dashed lines*) and Variance (*continuous lines*) parameters used for the classification; *blue continuous line* represents a flat area, while the *red* one is the variance of the slope, that is an unsafe area for the landing

allows to define a target area from a high resolution aerial or satellite image, hence to define the waypoints of the navigation trajectory or the landing area. Two algorithms for safe landing area detection are also proposed, based on the optical flow analysis. Results show the appropriateness of the vision based approach that does not require any artificial landmark and is robust to occlusions and light variations.

Future works are oriented to improve robustness of the whole system and specifically some important aspects of the landing task concerning with safety. The possibilities related to the optical flow techniques presented in the last part of the paper will be explored to obtain not only the simple evaluation of the landing area flatness, but even the capacity to actively search a safe zone. The first objective will be the detection of safe and unsafe areas from the same image.

The applications of such a system are notable; from exploration and rescue to target tracking and data acquisition.

References

1. Valavanis, K.: Advances in unmanned aerial vehicles: state of the art and the road to autonomy. Intelligent Systems, Control and Automation: Science and Engineering **33** (2007)
2. Bejar, M., Ollero, A., Cuesta, F.: Modeling and control of autonomous helicopters, advances in control theory and applications. Lect. Notes Control Inf. Sci. **353** (2007)
3. Lee, D., Jin Kim, H., Sastry, S.: Feedback linearization vs. adaptive sliding mode control for a quadrotor helicopter. Int. J. Control Autom. Syst. **7**(3), 419–428 (2009)
4. Bernard, M., Kondak, K., Hommel, G.: Framework for development and test of embedded flight control software for autonomous small size helicopters. Embedded Systems – Modeling, Technology, and Applications, pp. 159–168 (2006)
5. Monteriù, A., Asthana, P., Valavanis, K., Longhi, S.: Model-based sensor fault detection and isolation system for unmanned ground vehicles: theoretical aspects (part i and ii). In: Proceedings of the IEEE International Conference on Robotics and Automation (ICRA) (2007)
6. Conte, G., Doherty, P.: An integrated UAV navigation system based on aerial image matching. In: IEEE Aerospace Conference, pp. 1–10 (2008)
7. Luo, P., Pei, H.: An autonomous helicopter with vision based navigation. In: IEEE International Conference on Control and Automation (2007)
8. He, Z., Iyer, R.V., Chandler, P.R.: Vision-based UAV flight control and obstacle avoidance. In: American Control Conference (2006)
9. Mondragon, I.F., Campoy, P., Correa, J.F., Mejias, L.: Visual model feature tracking for UAV control. In: IEEE International Symposium on Intelligent Signal Processing, WISP (2007)
10. Campoy, P., Correa, J.F., Mondragón, I., Martínez, C., Olivares, M., Mejías, L., Artieda, J.: Computer vision onboard UAVs for civilian tasks. J. Intell. Robot. Syst. **54**(1–3), 105–135 (2009)
11. Caballero, F., Merino, L., Ferruz, J., Ollero, A.: Vision-based odometry and SLAM for medium and high altitude flying UAVs. J. Intell. Robot. Syst. **54**(1–3), 137–161 (2009)
12. Bethke, B., Valenti, M., How, J.: Cooperative vision based estimation and tracking using multiple UAVs. In: Advances in Cooperative Control and Optimization. Lect. Notes Control Inf. Sci., vol. 369, pp. 179–189 (2007)
13. Merz, T., Duranti, S., Conte, G.: Autonomous landing of an unmanned helicopter based on vision and inertial sensing. Experimental Robotics IX, Springer Tracts in Advanced Robotics, vol. 21, pp. 343–352 (2006)
14. Daquan, T., Hongyue, Z.: Vision based navigation algorithm for autonomic landing of UAV without heading & attitude sensors. In: Proceedings of the Third International IEEE Conference on Signal-Image Technologies and Internet-Based System, pp. 972–978 (2007)
15. Meingast, M., Geyer, C., Sastry, S.: Vision based terrain recovery for landing unmanned aerial vehicles. In: 43rd IEEE Conference on Decision and Control (CDC), vol. 2, pp. 1670–1675 (2004)

16. Shakernia, O., Vidal, R., Sharp, C.S., Ma, Y., Sastry, S.S.: Multiple view motion estimation and control for landing an unmanned aerial vehicle. In: Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), pp. 2793–2798 (2002)
17. Saripalli, S., Montgomery, J., Sukhatme, G.: Visually-guided landing of an unmanned aerial vehicle. IEEE Trans. Robot. Autom. **19**(3), 371–381 (2003)
18. Saripalli, S., Sukhatme, G.S.: Landing a helicopter on a moving target. In: IEEE International Conference on Robotics and Automation (ICRA), pp. 2030–2035 (2007)
19. Garcia-Padro, P.J., Sukhatme, G.S., Montgomery, J.F.: Towards vision-based safe landing for an autonomous helicopter. In: Robotics and Autonomous Systems, vol. 38, no. 1, pp. 19–29(11). Elsevier (2002)
20. Johnson, A., Montgomery, J., Matthies, L.: Vision guided landing of an autonomous helicopter in hazardous terrain. In: Proceedings of the IEEE International Conference on Robotics and Automation (2005)
21. Templeton, T., Shim, D.H., Geyer, C., Sastry, S.: Autonomous vision-based landing and terrain mapping using am MPC-controlled unmanned rotorcraft. In: Proceedings of the IEEE International Conference on Robotics and Automation, pp. 1349–1356 (2007)
22. Se, S., Lowe, D., Little, J.: Vision-based mobile robot localization and mapping using scale-invariant features. In: Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), pp. 2051–2058 (2001)
23. Lowe, D.: Distinctive image features from scale-invariant keypoints. Int. J. Comput. Vision **60**(2), 91–110 (2004)
24. Frontoni, E., Zingaretti, P.: Adaptive and fast scale invariant feature extraction. In: Second International Conference on Computer Vision Theory and Applications, Workshop on Robot Vision (2007)
25. Frontoni, E., Zingaretti, P.: Feature extraction under variable lighting conditions. CISI (2006)
26. Bramwell, A.R.S., Done, G., Balmford, D.: Bramwell's Helicopter Dynamics, 2nd edn. Butterworth Heinemann (2001)
27. Mancini, A., Cesetti, A., Iuale', A., Frontoni, E., Zingaretti, P., Longhi, S.: A framework for simulation and testing of UAVs in cooperative scenarios. In: International Symposium on Unmanned Aerial Vehicles (UAV'08) (2008)
28. Montgomery, J.: Learning helicopter control through "teaching by showing". Ph.D. Thesis, School of Comp. Sci., USC (1999)
29. Mataric, M.J.: Behavior-based control: examples from navigation, learning and group behavior. J. Exp. Theor. Artif. Intell. (Special Issue on Software Architecture for Physical Agents) **9**(2–3), 67–83 (1997)
30. Shim, D.H., Kirn, H.J., Sastry, S.: Hierarchical control system syntesys for rotorcraft-based unmanned aerial vehicles. In: AIAA Guidance, Navigation and Control Conference and Exhibit (2000)