Fuzzy Controller for UAV-landing task using 3D-position Visual Estimation

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Abstract—This paper presents a Fuzzy Control application for a landing task of an Unmanned Aerial Vehicle, using the 3Dposition estimation based on visual tracking of piecewise planar objects. This application allows the UAV to land on scenarios in which it is only possible to use visual information to obtain the position of the vehicle. The use of the homography allows a realtime estimation of the UAV's pose with respect to an helipad using a monocular camera. Fuzzy Logic allows the definition of a model-free control system of the UAV. The Fuzzy controller analyzes the visual information to generate altitude commands for the UAV in a landing task.

I. INTRODUCTION

The unmanned aerial vehicle (UAV) has made its way quickly and decisively to the forefront of current aviation technology. Opportunities exist in a broadening number of fields for the application of UAV systems as the components of these systems become increasingly lighter and more powerful. Of particular interest are those occupations that require the execution of missions which depend heavily on dull, dirty, or dangerous work, UAVs provide a cheap, safe alternative to manned systems and often provide a far greater magnitude of capability.

Computer vision has played and important role on the growing development of UAV, in which has been used as an important sensor, initially used for surveillance and then being integrated on the control system of the vehicle in order to use the rich information provided by visual systems as the main source of information for a vast list of applications, covering from visual control system based on regular cameras [13], [1] to autonomous landing [7], [19] and obstacle avoidance [10], [2].

In contrast to conventional control, fuzzy control was initially introduced as a model-free control design method based on a representation of the knowledge and the reasoning process of a human operator. Fuzzy logic can capture the continuous nature of human decision processes and as such is a definite improvement over methods based on binary logic (which are widely used in industrial controllers). Hence, it is not surprising that practical applications of fuzzy control started to appear very quickly after the method had been introduced in publications. Some of those applications of Fuzzy control and UAV are: for visual servoing [18], for an autopilot using a Fuzzy PID control [20], an obstacle avoidance and path planning system [8] and to manage a team of UAVs [25].

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Our research interest focuses on developing computer vision techniques to provide UAVs with an additional source of information to perform visually guided task - this includes tracking and visual servoing, inspection, autonomous landing and positioning, or ground-air cooperation. These situations need reliable state information, that allows a onboard controller to generate accurate positioning. In general the pose information is estimated based on the the GPS and the inertial measurement unit IMU sensor measurements. However, for low altitude tasks in urban scenarios, the estimation often is inaccurate because it is affected by GPS dropouts, thus making flying in these constrained environments more vulnerable and more prone to problems. Computer vision as passive sensor not only offers a rich source of information for navigational purposes, but it can be also used as a main navigational sensor in place of GPS. With the increasing interest in UAVs, a visual system that can determine the robot 3D location in its operational environment is becoming a key sensor for civil applications.

This paper presents a Fuzzy Controller which use the visual information obtained by a real time 3D-position estimation method, based on the tracking of a helipad using robust homographies estimation for descend in landing tasks. Section II explains the visual algorithm used in order to robustly track the reference landmark or helipad. Section III explains how the pose of a planar object relative to a moving camera coordinate center is obtained, using frameto-frame homographies and the projective transformation of the reference object on the image plane. The definition of the Fuzzy controller used to analyze the visual information estimated onboard the UAV is presented in Section IV. Finally, Section V shows the specifications of the Unmanned Helicopter, and the test results of the proposed algorithm running onboard a UAV, by comparing the estimated 3D pose data with the one given by the inertial Measurement Unit IMU. This validates our approach for an autonomous landing control based in visual information.

II. VISUAL PROCESSING

This section explains how the frame-to-frame homography is estimated using matched points and robust model fitting algorithms. For it, the pyramidal Lucas-Kanade optical flow [12] on corners detected using the method of Shi and Tomasi [21] is used to generate a set of corresponding points, then, a RANSAC [9] algorithm is used to robustly estimate projective transformation between the reference object and the image. Next section explains how this frame-to-frame is used to to obtain the 3D pose of the object with respect to the camera coordinate system.

On images with high motion, good matched features can be obtained using the well know Pyramidal Lucas-Kanade algorithm modification [12]. It is used to solve the problem that arise when large and non-coherent motion are present between consecutive frames, by first tracking features over large spatial scales on the pyramid image, obtaining an initial motion estimation, and then refining it by down sampling the levels of the images pyramid until it arrives at the original scale.

The set of corresponding or matched points between two consecutive images $((x_i, y_i) \leftrightarrow (x'_i, y'_i)$ for $i = 1 \dots n$,) obtained using the pyramidal Lucas-Kanade optical flow is used to compute the 3x3 matrix **H** that takes each $\bar{\mathbf{x}}_i$ to $\bar{\mathbf{x}}'_i$ or $\bar{\mathbf{x}}_i' = \mathbf{H}\bar{\mathbf{x}}_i$ or the Homography that relates both images. The matched points often have two error sources. The first one is the measurement of the point position, which follows a Gaussian distribution. The second one is the outliers to the Gaussian error distribution, which are the mismatched points given by the selected algorithm. These outliers can severely disturb the estimated homography, and consequently alter any measurement based on homographies. In order to select a set of inliers from the total set of correspondences so that the homography can be estimated employing only the set of pairs considered as inliers, robust estimation using Random Sample Consensus (RANSAC) algorithm [9] is used. It achieves its goal by iteratively selecting a random subset of the original data points by testing it to obtain the model and evaluating the model consensus, which is the total number of original data points that best fit the model. In the case of a Homography, four correspondences are enough to have a exact solution or minimal solution using the Inhomogeneous method [6]. This procedure is then repeated a fixed number of times, each time producing either a model which is rejected because too few points are classified as inliers, or a refined model. When total trials are reached, the algorithm returns the Homography with the largest number of inliers.

III. 3D ESTIMATION BASED ON HOMOGRAPHIES

This section shows how to estimate the 3D position of a world plane relative to the camera projection center for every image sequence using previous frame-to-frame homographies and the projective transformation at first, obtaining for each new image, the camera rotation matrix \mathbf{R} and a translational vector \mathbf{t} . This method is similar to the one propose by Simon *et. al.* [24], [23] and is deeply detail on [14].

A. World plane projection onto the Image plane

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Mondragon2010ICRA In order to align the planar object on the world space and the camera axis system, we consider the general pinhole camera model and the homogeneous camera projection matrix, that maps a world point \mathbf{x}_w in \mathbb{P}^3 to a point \mathbf{x}^i on i^{th} image in \mathbb{P}^2 , defined by equation 1:

$$\mathbf{x}^{i} = \mathbf{P}^{i} \mathbf{x}_{w} = \mathbf{K} [\mathbf{R}^{i} | \mathbf{t}^{i}] \mathbf{x}_{w} = \mathbf{K} \begin{bmatrix} \mathbf{r}_{1}^{i} & \mathbf{r}_{2}^{i} & \mathbf{r}_{3}^{i} & \mathbf{t}^{i} \end{bmatrix} \mathbf{x}_{w}$$
(1)

where the matrix **K** is the camera calibration matrix, \mathbf{R}^i and \mathbf{t}^i are the rotation and translation that relates the world coordinate system and camera coordinate system, and *s* is an arbitrary scale factor. Figure 1 shows the relation between a world reference plane and two images taken by a moving camera, showing the homography induced by a plane between these two frames.

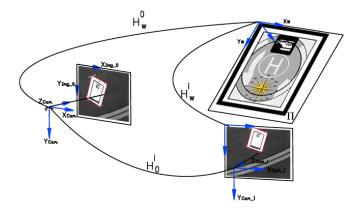


Fig. 1. Projection model on a moving camera and frame-to-frame homography induced by a plane.

If point \mathbf{x}_w is restricted to lie on a plane Π , with a coordinate system selected in such a way that the plane equation of Π is Z = 0, the camera projection matrix can be written as equation 2:

$$s\mathbf{x}^{i} = \mathbf{P}^{i}\mathbf{x}_{\Pi} = \mathbf{P}^{i} \begin{vmatrix} X \\ Y \\ 0 \\ 1 \end{vmatrix} = \langle \mathbf{P}^{i} \rangle \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix}$$
 (2)

where $\langle \mathbf{P}^i \rangle$ denotes that this matrix is deprived on its third column or $\langle \mathbf{P}^i \rangle = \mathbf{K} \begin{bmatrix} \mathbf{r}_1^i & \mathbf{r}_2^i & \mathbf{t}^i \end{bmatrix}$. The deprived camera projection matrix is a 3 × 3 projection matrix, which transforms points on the world plane (now in \mathbb{P}^2) to the *i*th image plane (likewise in \mathbb{P}^2), that is none other that a planar homography \mathbf{H}_w^i defined up to scale factor as equation 3 shows.

$$\mathbf{H}_{w}^{i} = \mathbf{K} \begin{bmatrix} \mathbf{r}_{1}^{i} & \mathbf{r}_{2}^{i} & \mathbf{t}^{i} \end{bmatrix} = \langle \mathbf{P}^{i} \rangle$$
(3)

Equation 3 defines the homography which transforms points on the world plate to the i^{th} image plane. Any point on the world plane $\mathbf{x}_{\Pi} = [x_{\Pi}, y_{\Pi}, 1]^T$ is projected on the image plane as $\mathbf{x} = [x, y, 1]^T$. Because the world plane coordinates system is not know for the i^{th} image, \mathbf{H}_w^i can not be directly evaluated. However, if the position of the word plane for a reference image is known, a homography \mathbf{H}_w^0 , can be defined. Then, the i^{th} image can be related with the reference image to obtain the homography \mathbf{H}_0^i . This mapping is obtained using sequential frame-to-frame homographies \mathbf{H}_{i-1}^i , calculated for any pair of frames (i-1,i) and used to relate the i^{th} frame to the first image \mathbf{H}_0^i using equation 4:

$$\mathbf{H}_{0}^{i} = \mathbf{H}_{i-1}^{i} \mathbf{H}_{i-2}^{i-1} \cdots \mathbf{H}_{0}^{1}$$

$$\tag{4}$$

This mapping and the aligning between initial frame to world plane reference is used to obtain the projection between the world plane and the i^{th} image $\mathbf{H}_{w}^{i} = \mathbf{H}_{0}^{i}\mathbf{H}_{w}^{0}$. In order to relate the world plane and the i^{th} image, we must know the homography \mathbf{H}_{w}^{0} . A simple method to obtain it, requires to match four points on the image with the corresponding corners of the rectangle in the scene, forming the matched points $(0,0) \leftrightarrow (x_1,y_1), (0,\Pi_{Width}) \leftrightarrow (x_2,y_2),$ $(\Pi_{Lenght}, 0) \leftrightarrow (x_3, y_3)$ and $(\Pi_{Lenght}, \Pi_{Width}) \leftrightarrow (x_4, y_4)$. This process can be done by both, a helipad frame and corners detector or by an operator through a ground station interface. The helipad points selection generates a world plane defined in a coordinate frame in which the plane equation of Π is Z = 0. With these four correspondences between the world plane and the image plane, the minimal solution for homography $\mathbf{H}_{w}^{0} = \begin{bmatrix} \mathbf{h}_{1w}^{0} & \mathbf{h}_{2w}^{0} & \mathbf{h}_{3w}^{0} \end{bmatrix}$ is obtained.

B. Translation Vector and Rotation Matrix

The rotation matrix and the translation vector are computed from the plane to image homography using the method described in [28].

From equation 3 and defining the scale factor $\lambda = 1/s$, we have that

$$\begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \mathbf{t} \end{bmatrix} = \lambda \mathbf{K}^{-1} \mathbf{H}_w^i = \lambda \mathbf{K}^{-1} \begin{bmatrix} \mathbf{h}_1 & \mathbf{h}_2 & \mathbf{h}_3 \end{bmatrix}$$

where
$$\mathbf{r}_1 = \lambda \mathbf{K}^{-1} \mathbf{h}_1, \quad \mathbf{r}_2 = \lambda \mathbf{K}^{-1} \mathbf{h}_2, \quad \mathbf{t} = \lambda \mathbf{K}^{-1} \mathbf{h}_3$$
(5)

The scale factor is calculated as $\lambda = \frac{1}{\|\mathbf{K}^{-1}\mathbf{h}_1\|}$.

Because the columns of the rotation matrix must be orthonormal, the third vector of the rotation matrix \mathbf{r}_3 could be determined by the cross product of $\mathbf{r}_1 \times \mathbf{r}_2$. However, the noise on the homography estimation causes that the resulting matrix $\mathbf{R} = [\mathbf{r}_1 \ \mathbf{r}_2 \ \mathbf{r}_3]$ does not satisfy the orthonormality condition and we must find a new rotation matrix \mathbf{R}' that best approximates to the given matrix \mathbf{R} according to smallest Frobenius norm for matrices (the root of the sum of squared matrix coefficients) [26] [28]. As demonstrated by [28], this problem can be solved by forming the Rotation Matrix $\mathbf{R} = [\mathbf{r}_1 \ \mathbf{r}_2 \ (\mathbf{r}_1 \times \mathbf{r}_2)] = \mathbf{USV}^T$ and using singular value decomposition (SVD) to form the new optimal rotation matrix $\mathbf{R}' = \mathbf{UV}^T$.

The solution for the camera pose problem is defined as $\mathbf{x}^i = \mathbf{P}^i \mathbf{X} = \mathbf{K}[\mathbf{R}'|\mathbf{t}]\mathbf{X}$. The translational vector obtained is already scaled based on the dimensions defined for the reference plane during the alignment between the helipad and image I_0 , so if the dimensions of the world rectangle are defined in *mm*, the resulting vector $\mathbf{t}^i_w = [x, y, z]^t$ is also in *mm*. In [14], it is show how the Rotation Matrix can be decomposed in order to obtain the Tait-Bryan or Cardan Angles, which is one of the preferred rotation sequences in flight and vehicle dynamics. Specifically, these angles are formed by the sequence: (1) ψ about z axis (yaw $\mathbf{R}_{z,\psi}$), (2) θ about y_a (pitch $\mathbf{R}_{y,\theta}$), and (3) ϕ about the final x_b axis (roll $\mathbf{R}_{x,\phi}$), where a and b denote the second and third stage in a three-stage sequence or axes.

C. Estimation Filtering.

An extended Kalman Filter (EKF) has been incorporated in the 3D pose estimation algorithm in order to smooth the position and correct the errors caused by the homography drift along time. The state vector is defined as the position $[x_{\mathbf{k}}, y_{\mathbf{k}}, z_{\mathbf{k}}]$ and velocity $[\Delta x_{\mathbf{k}}, \Delta y_{\mathbf{k}}, \Delta z_{\mathbf{k}}]$ of the k^{th} helipad expressed in the onboard camera coordinate system. We consider the dynamic model as a linear system where system has constant velocity, as presented in the following equations:

$$\mathbf{x}_{\mathbf{k}} = \mathbf{F}\mathbf{x}_{\mathbf{k}-1} + \mathbf{w}_{\mathbf{k}} \tag{6}$$

$$\begin{bmatrix} x_{\mathbf{k}} \\ y_{\mathbf{k}} \\ z_{\mathbf{k}} \\ \Delta x_{\mathbf{k}} \\ \Delta y_{\mathbf{k}} \\ \Delta z_{\mathbf{k}} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta t & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta t \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_{\mathbf{k}-1} \\ y_{\mathbf{k}-1} \\ z_{\mathbf{k}-1} \\ \Delta x_{\mathbf{k}-1} \\ \Delta y_{\mathbf{k}-1} \\ \Delta y_{\mathbf{k}-1} \\ \Delta z_{\mathbf{k}-1} \end{bmatrix} + \mathbf{w}_{t-1}$$

$$(7)$$

Where \mathbf{x}_{k-1} is the state vector (position and velocity), **F** is the system matrix, **w** the process noise, and Δt represents the time step.

Because the visual system only estimates the position of the helipad, the measurements are expressed as follows:

$$\mathbf{z}_{\mathbf{k}} = \begin{bmatrix} \bar{x}_{\mathbf{k}} \\ \bar{y}_{\mathbf{k}} \\ \bar{z}_{\mathbf{k}} \end{bmatrix} + \mathbf{v}_{\mathbf{k}}$$
(8)

Where $\mathbf{z}_{\mathbf{k}}$ is the measurement vector and $[\bar{x}_{\mathbf{k}}, \bar{y}_{\mathbf{k}}, \bar{z}_{\mathbf{k}}]^{T}$ is the position of the helipad with respect to the camera coordinate system and $\mathbf{v}_{\mathbf{k}}$ is measurement noise. With the previous definitions, the two phases of the filter Prediction and Correction can be formulated as presented in [27], assuming that the process noise $\mathbf{w}_{\mathbf{k}}$ and the measurement noise $\mathbf{v}_{\mathbf{k}}$ are white, zero-mean, Gaussian noise with covariance matrix \mathbf{Q} and \mathbf{R} , respectively.

The output of the filter is the smoothed position of the helipad, that will be used as input for the control system.

IV. FUZZY CONTROLLER SYSTEM

This Section presents the implementation of the Mamdani Fuzzy controller which analyzes the visual information in order to generate descend commands for the UAV (velocity commands in meters per seconds).

The MOFS has been designed by the definition of one class for each part of the fuzzy-logic environment (variables, rules, membership functions and defuzzification modes) in order to facilitates the future updates and to make easier work with it. In the Figure refclases are shown the different classes and the structure of the software implementation in a UML diagram. The boxes are divided in three parts and show, in the upper part, the name of the class, in the middle part, the attribute of the class, and in the bottom part,the methods or operations. Currently, three different subtype of membership functions have been implemented, those are the pyramidal, the trapezoidal and the gaussian. Furthermore,for

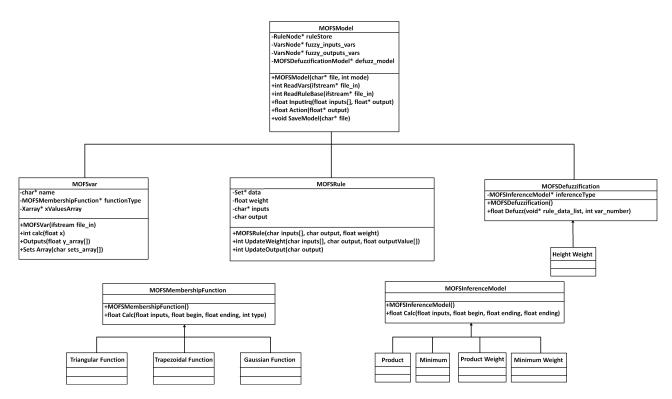


Fig. 2. Classes structure of the Miguel Olivares' Fuzzy Software.

the defuzzification phase the Height weight method is used (Eq. 9).

$$y = \frac{\sum_{l=1}^{M} \overline{y}^{l} \prod \left(\mu_{B'}(\overline{y}^{l}) \right)}{\sum_{l=1}^{M} \prod \left(\mu_{B'}(\overline{y}^{l}) \right)}$$
(9)

Additionally, the four subtypes of inference models for the fuzzification that have been implemented are the maximum and the product with and without taking into account the rule-weight characteristic of each rule. The weight of each rule is a part of a learning algorithm based on the idea of the synaptic weights of the neurons, but for this work this improvement is not used, in [17] and [16] is possible to see how it works. With this learning algorithm is possible to adapt the base of rules to a particular behavior, by reading patterns of inputs and its corresponding correct output.

More details about the structure of this software can be found in [15].

The controller is implemented for control the altitude of the UAV in order to be capable to made an auto-landing. This controller is working inside the vision-computer, that is onboard the UAV. Are defined two inputs and one output for the fuzzy controller. For the definition of the variables an heuristic method is used. The data is acquired from different manual and hover flight tests. The two inputs are: the estimation of the altitude, that is made by the homography (Fig. 3), and the variation of this value between the last two frames (Fig. 4). For this last input is taking into account possible variation of the frame-rate of the camera in the last second, in order to keep it more robust for possible changes of the frame-rate caused by some computer operations. The output of the controller is the velocity command to send to aircraft to approximate to the helipad location (Fig. 5).

The control is made based on camera configuration, like a eye-to-hand configuration, because the camera is fixed on the UAV. The position of the camera respect the robot, the configuration of the system is an *eye-in-hand* type, and talking about the architecture of the visual and servo system, the implementation is based on a *dynamic look-and-move* visual control, that sends commands on velocity, because the 3D pose is estimated using the homography, taking into account the characteristic of the helipad and the intrinsic parameters of the camera, and, then, the controller sends velocity commands to move the UAV.

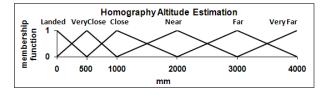


Fig. 3. Estimation of the altitude (in mm), based on the homography of the helipad.

V. TESTS AND RESULTS

This section shows the specification of the UAV, and the landing and pose estimation tests.

The Colibri project has three operational UAV platforms: one electric helicopter and two gasoline-powered helicopters [5] (figure (6)). The COLIBRI testbeds [1] are equipped with

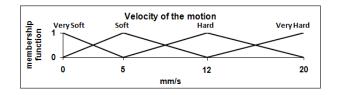


Fig. 4. Velocity of the position changes (in mm/s), tacking into account the estimation of the homography and the frame-rate of each moment.

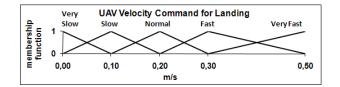


Fig. 5. Output of the Fuzzy Controller, the velocity commands for the UAV in m/s

an Xscale-based flight computer augmented with sensors (GPS, IMU, Magnetometer, fused with a Kalman filter for state estimation). Additionally they include a pan and tilt servo-controlled platform for many different cameras and sensors. In order to enable it to perform vision processing, it also has a VIA mini-ITX 1.5 GHz onboard computer with 2 Gb RAM, a wireless interface, and support for many Firewire cameras including Mono (BW), RAW Bayer, color, and stereo heads.



Fig. 6. COLIBRI III Electric helicopter UAV used for pose estimation tests.

The system runs in a client-server architecture using TCP/UDP messages. The computers run Linux OS working in a multi-client wireless 802.11g ad-hoc network, allowing the integration of vision systems and visual tasks with flight control. This architecture allows embedded applications to run onboard the autonomous helicopter while it interacts with external processes through a high level switching layer. The visual control system and additional external processes are also integrated with the flight control through this layer using TCP/UDP messages, forming a *dynamic look-and-move* [11] servoing architecture as is explained on Section IV and is shown in figure 7. The helicopter's low-level controller is based on PID control loops to ensure its stability. Because features are extracted in the image and then used to estimate the pose of the helipad or target with respect to the camera coordinate system (fixed on the UAV camera platform), our control scheme is considered to be Position Base Visual Servoing (PBVS) system [11], [4], [22]. In this kind of control, an error between the current and the desired pose of

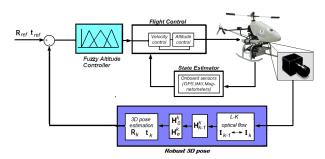


Fig. 7. UAV onboard visual control system following a *dynamic look-and-move* architecture

the camera-UAV is calculated and used by a fuzzy controller to generate the velocity references used by the low level controller to descend the UAV.

For these test a Monocromo CCD Firewire camera with a resolution of 640x480 pixels is used. The camera is calibrated before each test, so the intrinsic parameters are know. The camera is installed in such a way that it is looking downward with relation to the UAV. A known rectangular helipad is used as the reference object to which estimate the UAV 3D position. It is aligned in such a way that its axes are parallel to the local plane North East axes. This helipad was designed in such a way that it produces many distinctive corners for the visual tracking. Figure 8, shows the helipad used and the coordinate systems involved in the pose estimation. For

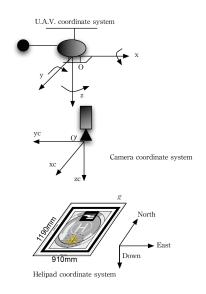


Fig. 8. Helipad, camera and U.A.V coordinate systems

these tests a series of landing flights in autonomous mode at different heights were done. Figure 9 shows the first frame for tree different test. The test begins when the UAV is hovering over the helipad. Then a user (through the ground station interface) manually selects four point on the image that corresponds to four corners on the helipad, forming the matched points $(0,0) \leftrightarrow (x_1,y_1)$, $(910mm,0) \leftrightarrow (x_2,y_2)$, $(0,1190mm) \leftrightarrow (x_3,y_3)$ and $(910mm,1190mm) \leftrightarrow (x_4,y_4)$. This manual selection generates a world plane defined in a coordinates frame in which the plane equation of Π is Z = 0and also defining the scale for the 3D results. With these four correspondences between the world plane and the image plane, the minimal solution for homography \mathbf{H}_{w}^{0} is obtained. Then, the UAV is moved, making changes on Z axis, (X,Y axes are controlled by the autopilot, maintaining a hovering condition while the helicopter is descending). The helipad is constantly tracking by estimating the frame-to-frame homographies \mathbf{H}_{i-1}^{i} , which is used to obtain the homographies \mathbf{H}_{0}^{i} , and \mathbf{H}_{w}^{i} from which \mathbf{R}_{w}^{i} and \mathbf{t}_{w}^{i} is estimated. The 3D poses estimation process is done with an average of 12 frames per second FPS.

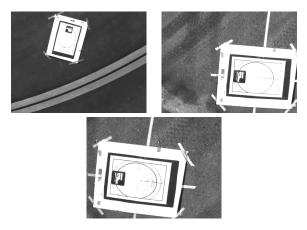


Fig. 9. Helipad position on each of the different landing tests. The helipad is oriented in such a way that the X axis is the North position, the Y axis is the East position and Z axis is the Down Position (Earth center).

Figure 10 shows a landing sequence in which the 3D pose estimation based on a reference helipad is constantly estimated. The landing test begins when the UAV is hovering with an altitude of 5.2m, the figure shows the approach sequence when the helicopter is descending on the helipad. This figure also shows the original reference image, the current frame, the optical flow between last and current frame, the helipad coordinates in the current frame camera coordinate system and the Tait-Bryan angles obtained from the rotation matrix. Figure 11 shows the reconstruction of the flight test 1, using the IMU data.

The 3D pose estimated using the visual system is compared with helicopter position estimated by the controller, with reference to the takeoff point (Center of the Helipad). Because the local tangent plane to the helicopter is defined in such a way that the X axis is the North position, the Y axis is the East position and Z axis is the Down Position (negative), the measured X and Y values must be rotated according with the helicopter heading or Yaw angle, in order to be comparable with the estimated values obtained from the homographies. Figure 12 shows the estimated distance from the landmark with respect to the UAV during the descending approach and figure 13, shows the estimated yaw angle.

Results show a good performance of the visual estimated values compared with the IMU data. In general, estimated and IMU data have the same behavior for test sequences. The estimated altitude position Z have a error for flight 1

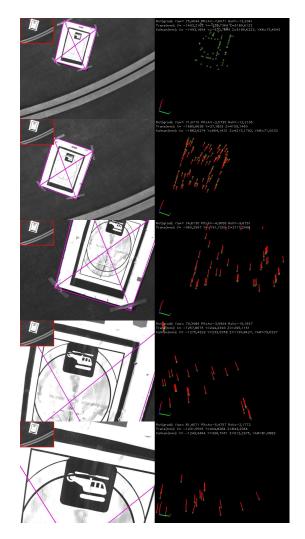


Fig. 10. 3D pose estimation based on a helipad tracking using Robust Homography estimation during a UAV landing process. Landing flight test beginning at an altitude of 5.2m. For all images, the reference image I_0 is on the small rectangle on the upper left corner. Left it the current frame and Right the Optical Flow between the actual and last frame. Superimposed are the projection of the original rectangle, the translation vector and the Tait-Bryan angles.

with a RMSE of 0.32m, 0.23m in test 2 and 0.13m in test 3, showing a good performance of the estimator during the landing phase. Finally, the yaw angle is correctly estimated, presenting a maximum error of 5.6° between the IMU and the estimated data.

Results also have shown that the system correctly estimates the 3D position when a maximum of the 70 % of the landmark is out of the field of view of the camera (zoom). On Colibri project web pages [5] and [3] are available some videos showing these tests and the performance of the proposed system.

VI. CONCLUSIONS

An approach of the application of landing task using only vision for UAV is presented in this paper. The 3D-position estimation of the UAV is acquired using the homography of an specific helipad. This visual information is analyzed by

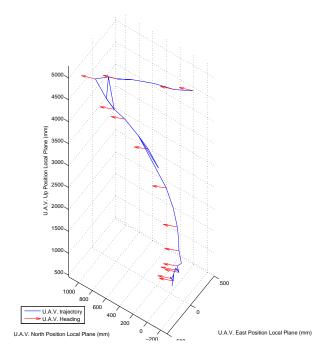


Fig. 11. 3D flight and heading reconstruction for the flight sequence show on figure 10 (flight test 1)

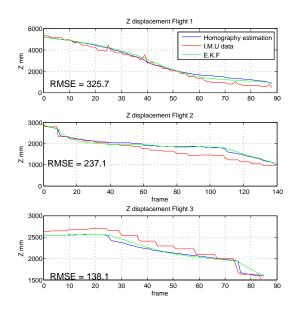


Fig. 12. Comparison between the Z axis displacement for homography estimation and IMU data.

a Fuzzy controller in order to generate the commands for control the altitude of the unmanned helicopter to land on the helipad. The presented results shown a descend from a long distance, more than 5 meters, to the floor, obtaining the visual information even just the 30% of the helipad is in the camera field of view as is show in the last frame of the sequence. The optimal visual information allows to carry out the landing task in scenarios where the GPS dropouts make this task impossible to be accomplished. Furthermore, the obtained altitude information is more precise than the GPS-IMU onboard system, as are shown in real tests.

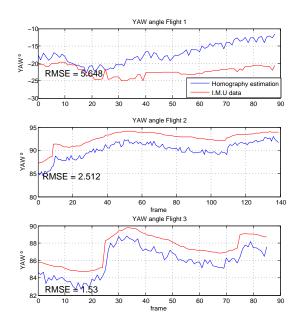


Fig. 13. Comparison between the *Yaw* angle measured using homography estimation and IMU data.

Future work includes to implement other Fuzzy controllers for the other possible movements of the UAV (Forward, Side and heading), in order to perform a total autonomous landing task in all axis. Use the implemented learning algorithm of the MOFS to improve the base of rules by the adaptation to manual flight. In addition, we are currently testing improved versions of the Lucas-Kanade optical flow, like the Inverse compositional algorithm (ICA) as well as evaluating the use of a different Kalman Filters for improved the 3D pose estimation.

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