Robust Cooperative UAV Visual SLAM

A. Nemra[*] and N. Aouf[**]
Department of Informatics and Sensors,
Cranfield University, UK
[*]a.nemra@cranfield.ac.uk, [**]n.aouf@cranfield.ac.uk

Abstracts
This paper aims at proposing a framework for Airborne Cooperative Visual Simultaneous Localization and Mapping (C-VSLAM). The use of cooperative vehicles presents many advantages over single-vehicle architecture. We present a nonlinear H∞ filtering scheme adapted to multiple Unmanned Aerial Vehicle (UAV) VSLAM based on the extension of a robust single vehicle VSLAM solution. Loop closure concept, based on revisited features is described with feature uncertainty analysis. Comparisons between single and multiple UAV VSLAM are made using realistic simulation scenario.
Keywords: SLAM, Nonlinear H∞ filter, UAV, loop closure, feature uncertainty.

1. Introduction

In the last decade, Unmanned Aerial Vehicles (UAVs) have attracted significant interest in a wide range of military and civilian applications [1]. Vision has been used as the perception tool for UAVs, as presented in [2] and [3], for relative position sensing and as in [4] for safe vehicle landing. New developments in UAV applications such as search and rescue [5], surveillance and exploration [6], [7], where large area coverage ability is required, involve the use of multiple autonomous aerial vehicles.

In these tasks, aerial vehicles are often required to operate in unknown environment, where navigation maps are unavailable and where GPS signals may be denied. In this latter case, Inertial Navigation System (INS) could be used on its own. However, eventual growth in INS errors is prohibitive to many applications. Instead, an aided INS with stereo vision system can be used on each UAV where the INS localisation errors are corrected and an online map generation is performed. This is what we call here the paradigm of Visual Simultaneous Localisation and Mapping (VSLAM). Development of SLAM algorithms has been the focus of research in robotics in the last few years [8], [9], [10]. Extensive research works, employing Extended Kalman Filter (EKF), have been reported in the literature to address several aspects of the single vehicle SLAM problem [11].

In many applications, a single sensing platform may not be sufficient for collecting data or creating maps of an unknown environment. Fleets of autonomous Underwater Vehicles (AUVs) [12] and Unmanned Aerial Vehicles (UAVs) [13] have been proposed for applications ranging from environmental monitoring through surveillance to defence. These unmanned systems require the ability to share information and to fuse information from different sources into a consistent picture of the environment [14]. Deploying multiple vehicles and providing them with a mechanism of sharing information can provide higher data rates, increase robustness, and minimize the chance of catastrophic system failure.

Multiple vehicle SLAM problem has been considered in the past, [15], [16] with a centralized architecture where all vehicles send their sensor data to a central Kalman filter. However, SLAM architectures based on Extended Kalman filters are very sensitive to outliers and the lower bound, for the map accuracy, presented in [17] is violated due to errors introduced during the linearization process. As a consequence the EKF SLAM produces inconsistent estimates [18][17]. Thus, proposing a nonlinear H∞ filtering scheme, which does not make assumptions on the noise statistics while minimizing the linearization effects as a base of our multiple vehicle VSLAM solution in this paper is legitimate and even sometimes required.

The outline of this paper is as follows: Section 2 develops the single UAV Visual SLAM process and observation model based on stereo camera system. In section 3, the proposed architecture of the cooperative UAV Visual SLAM is presented with the advantage of using Multiple UAV VSLAM with the loop closure concept. Finally, in section 5, simulation results using realistic scenarios are presented and a comparison between a single UAV VSLAM and multiple UAV VSLAM is made.

2. Single UAV Visual SLAM

The single vehicle VSLAM algorithm as shown in [18], is formulated using Extended Kalman Filter (EKF) and Nonlinear H∞ (NH∞) Filter in [18][19]. In both algorithms the map feature locations and the vehicle's position, velocity and attitude are estimated using relative observations between the vehicle and each feature using stereo vision system. In this paper, we will adopt the NH∞ algorithm to solve the VSLAM problem rather than Extended Kalman Filter (EKF) based VSLAM. The former presents more robustness and consistency comparing to the EKF based VSLAM solution [1].

In this section, we briefly cover the basics of the NH∞ based VSLAM algorithm. More details can be found in [18].

a- State Vector

The estimated state vector x_k at times k contains the three dimensional vehicle position (p^n), velocity (v^b) and Euler angles ($\Psi^n = [\phi, \theta, \psi]$) and the N three-dimensional feature locations (m_i^n) in the environment:

$$\hat{x}(k) = \begin{bmatrix} p_k^n \\ v_k^b \\ \Psi_k^n \\ m_{1,k}^n \\ \vdots \\ m_{N,k}^n \end{bmatrix}$$ where i = 1, ..., N and the superscript n indicates the vector is referenced in the navigation frame, and b indicates the vector is referenced in the body frame. The body frame is the same as the UAV frame. The navigation frame is fixed w.r.t the surface of the Earth and is placed arbitrarily within the operating area of the vehicle, with x-axis pointing north, y-axis pointing east and z-axis pointing down towards the centre of the Earth. Fig.1 illustrates different frames used to solve the airborne VSLAM using stereo vision system.

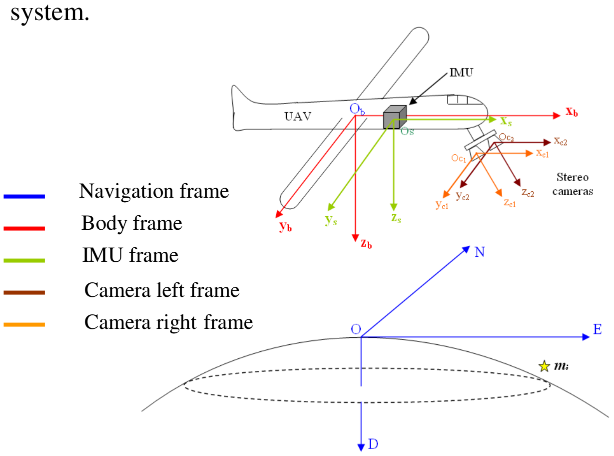


Fig. 1 UAV with IMU& stereo cameras

b- Process Model

The state estimate $x(k)$ at times k is predicted forward in time by integrating Inertial Measurement Unit (IMU) readings using an inertial frame mechanisation of the inertial navigation equations as:

$$\begin{bmatrix} p_k^n \\ v_k^b \\ \Psi_k^n \end{bmatrix} = \begin{bmatrix} p_{k-1}^n + C_{nb} \cdot v_k^n \cdot \Delta t \\ v_{k-1}^b + [f_k^b + v_{k-1}^b \times w_k^b - C_{nb}^T \cdot g^n] \cdot \Delta t \\ \Psi_{k-1}^b + E_{nb} \cdot w^b \cdot \Delta t \end{bmatrix} \quad (1)$$

where f^b and w^b are the body-frame referenced vehicle accelerations and rotation rates from the IMU and g^n is the acceleration due to gravity. C_{nb} and E_{nb} are the direction cosine matrix and rotation rate transformation matrix from body to navigation frame respectively. More details about the process model are given in [20][18].

Scene visual Feature locations are assumed to be stationary in the navigation frame and thus the process model for the position of the j^{th} feature is:

$$m_{j,k}^n = m_{j,k-1}^n$$

The problem with the navigational solution provided by INS, Fig.2, is that it drifts with time as in most other dead reckoning systems. The drift rate of the inertial position is typically a cubic function of time. Small errors in gyros will be accumulated in angle estimates (roll and pitch), which in turn misrepresent gravitational acceleration as the vehicle acceleration and results in quadratic velocity (and cubic position) errors.

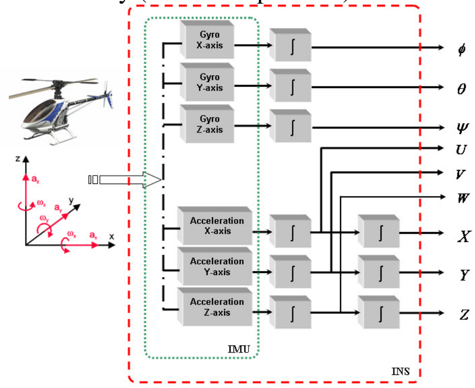


Fig.2 INS architecture

c- Stereo Vision Observation Model

Computer vision becomes vital for automatic perception and recognition of the environment especially for mapping in aerial robotics applications. Stereoscopic vision is broadly defined as the recovery of three-dimensional characteristics of a scene from multiple images taken from two different viewpoints, Fig.1. Stereo system is an attractive source of information for machine perception because it leads to direct range measurements, and unlike monocular approaches, does not merely infer depth or orientation through the use of photometric and statistical assumptions.

Once the stereo images are brought into point-to-point correspondence, recovering range values is relatively straightforward. Another advantage is that stereo is a passive method. Although active ranging methods that use structured light, laser range finders, or other active sensing techniques are useful in tightly controlled domains such as industrial automation applications, they are clearly limited in use for some outdoor aerial vision problems.

The observation model proposed in this paper is based on stereo vision cameras and is detailed in [18]. The **observation model,** linking the perceived visual landmarks to the SLAM state vector is given by:

$$\begin{cases} u_1 = \dfrac{m_{11}^{c1} x_{mi}^n + m_{12}^{c1} y_{mi}^n + m_{13}^{c1} z_{mi}^n + m_{14}^{c1}}{m_{31}^{c1} x_{mi}^n + m_{32}^{c1} y_{mi}^n + m_{33}^{c1} z_{mi}^n + m_{34}^{c1}} \\ v_1 = \dfrac{m_{21}^{c1} x_{mi}^n + m_{22}^{c1} y_{mi}^n + m_{23}^{c1} z_{mi}^n + m_{24}^{c1}}{m_{31}^{c1} x_{mi}^n + m_{32}^{c1} y_{mi}^n + m_{33}^{c1} z_{mi}^n + m_{34}^{c1}} \\ u_2 = \dfrac{m_{11}^{c2} x_{mi}^n + m_{12}^{c2} y_{mi}^n + m_{13}^{c2} z_{mi}^n + m_{14}^{c2}}{m_{31}^{c2} x_{mi}^n + m_{32}^{c2} y_{mi}^n + m_{33}^{c2} z_{mi}^n + m_{34}^{c2}} \\ v_2 = \dfrac{m_{21}^{c2} x_{mi}^n + m_{22}^{c2} y_{mi}^n + m_{23}^{c2} z_{mi}^n + m_{24}^{c2}}{m_{31}^{c2} x_{mi}^n + m_{32}^{c2} y_{mi}^n + m_{33}^{c2} z_{mi}^n + m_{34}^{c2}} \end{cases} \quad (2)$$

where $[x_{mi}^n \quad y_{mi}^n \quad z_{mi}^n]^T$ is the coordinate of the landmark m_i in the navigation frame, North/East/Down

(NED). m_{ij}^{c1} and m_{ij}^{c2} are the components of the projection matrix of camera right and camera left respectively [18]. Association of data in this work is assumed known as we deal with simulation data only.

d- Estimation process

The estimation process uses the process and observation models described in the previous subsections in a nonlinear filter to estimate the state x_k from observations y_k.

$$x_k = f(x_{k-1}, u_{k-1}) + g(x_{k-1})w_{k-1}$$
$$y_k = h(x_k, v_k) \tag{3}$$

f is the discrete version of Eq. 1 (in addition to elements of the landmarks states), *g* is a nonlinear function, x_k is the state at time step *k*, w_k is some additive process noises, y_k is the observation made at time *k*, v_k is some additive observation noises, *h* is the stereo observation model. The objective of the filtering technique is to estimate x_k using available observations y_k.

The non-linear vehicle model and observation model can be expanded about the filtered and predicted estimates of $\hat{x}_k$ and $\hat{x}_{k-1}$ as:

$$x_k = f(\hat{x}_{k-1/k-1}, u_k) + \nabla f_k(x)[x_k - \hat{x}_{k/k}] + \\ + \Delta_1(x_k - \hat{x}_{k/k}) + [\nabla f_w(x) + \Delta_2(x_k - \hat{x}_{k/k})]w_k \tag{4}$$

$$y_k = h(\hat{x}_{k/k-1}, u_k) + \nabla h_k(x)[x_k - \hat{x}_{k/k-1}] + \\ + \Delta_3(x_k - \hat{x}_{k/k-1}) + v_k \tag{5}$$

where $\nabla f_k(x)$ is the Jacobian of f evaluated at x_{k-1}, $\nabla f_w(x)$ the Jacobian of f / w_k evaluated at x_{k-1} and $\nabla h_k(x)$ is the Jacobian of h evaluated at x_{k-1} and Δ_i represent higher order terms of the Taylor series expansion. These higher order terms are norm bounded as: $\|\Delta_i\| \le \delta_i$.

The state and observation model may be rewritten as:

$$x_{k+1} = F_k x_k + \Gamma_k w_k + \Omega_k + \Delta_1(\tilde{x}_{k/k}) + \Delta_2(\tilde{x}_{k/k})w_k$$
$$y_k = H_k x_k + v_k + \Psi_k + \Delta_3(\tilde{x}_{k/k-1}) \tag{6}$$

with

$F_k = \nabla f_k(\hat{x}_{k/k})$, $\Gamma_k = \nabla f_w(\hat{x}_{k/k})$, $H_k = \nabla h_k(\hat{x}_{k/k-1})$, $\Omega_k = f(\hat{x}_{k/k}) - F_k \hat{x}_{k/k}$ and $\Psi_k = h(\hat{x}_{k/k-1}) - H_k \hat{x}_{k/k-1}$.

$$\hat{x}_{k+1} = F_k \hat{x}_k + \Gamma_k w_k + \Omega_k + \Pi_k \tag{7}$$

$$y_k = H_k x_k + v_k + \Psi_k + \Sigma_k \tag{8}$$

where

$$\Pi_k = \Delta_1(\tilde{x}_{k/k}) + \Delta_2(\tilde{x}_{k/k})v_k \tag{9}$$

and

$$\Sigma_k = \Delta_3(\tilde{x}_{k/k-1}) \tag{10}$$

These inputs must satisfy these norm bounds:

$$\|\Pi_k\|_2^2 \le \delta_1^2 \|\tilde{x}_{k/k}\|_2^2 + \delta_2^2 \|w_k\|_2^2 \tag{11}$$

and

$$\|\Sigma_k\|_2^2 \le \delta_3^2 \|\tilde{x}_{k/k}\|_2^2 \tag{12}$$

Instead of solving for the non-linear process and observation models, which contain the extra terms Π_k and Σ_k that are not used in the EKF formulation, the following scaled $H\infty$ problem is considered:

$$\hat{x}_{k+1} = F_k \hat{x}_k + \Gamma_k c_v w_k + \Omega_k \tag{13}$$

$$y_k = H_k x_k + c_w v_k + \Psi_k \tag{14}$$

where $c_w^2 = 1 - \gamma^2 \delta_1^2 - \gamma^2 \delta_3^2$ and $c_v^2 = c_w^2 (1 + \delta_1^2)^{-1}$.

This final form, Eq. 13,14, results in the same structure of the Extended Kalman Filter (EKF) [1] except that the error covariance correction of the linear $H\infty$ filter is used with the noise process w_k and v_k scaled by c_w and c_v.

3. Cooperative Multiple UAV Visual SLAM

In the multi-vehicle SLAM problem proposed in this paper, the estimated state becomes the position, velocity and attitude of the multiple vehicles and the positions of point features in the environment. In this section, we extend the single vehicle VSLAM, presented above, to the multiple vehicle case to see how we could improve UAV navigation results.

The VSLAM state vector and Jacobian matrix are given by:

- State vector

$$X_k = \begin{bmatrix} X_{uav1,k} \\ \vdots \\ X_{uavM,k} \\ m_{1,k}^n \\ m_{2,k}^n \\ \vdots \\ m_{N,k}^n \end{bmatrix}$$

- Jacobian matrix of f w.r.t X

$$F_{sys} = \begin{bmatrix} F_{uav1,k} & 0_{9\times9} & \cdots & 0_{9\times3N} \\ 0_{9\times9} & \ddots & 0_{9\times9} & \vdots \\ \vdots & 0_{9\times9} & F_{uavM,k} & 0_{9\times3N} \\ 0_{3N\times9} & \cdots & 0_{3N\times9} & I_{3N\times3N} \end{bmatrix}$$

- Jacobian matrix of f w.r.t w_k

$$\Gamma_{sys} = \begin{bmatrix} \Gamma_{uav1} & 0_{9\times6} & 0_{9\times6} \\ 0_{9\times6} & \ddots & 0_{9\times6} \\ 0_{9\times6} & 0_{9\times6} & \Gamma_{uavM} \\ 0_{3N\times6} & 0_{3N\times6} & 0_{3N\times6} \end{bmatrix}$$

- Jacobian matrix of h w.r.t X

$$H_{sys} = [0_{4\times9(i-1)} \quad H_{uav\_i} \quad 0_{4\times9(M-i)} \quad 0_{4\times9(j-1)} \quad H_{feature\_j} \quad 0_{4\times9(N-j)}]$$

for the i^{th} UAV and the j^{th} feature.

- Jacobian matrix of f w.r.t v_k

$V_{sys} = [I_{4\times4}]$

The cooperative VSLAM algorithm based on the Nonlinear H∞ filter is summarized below:

Assume we have ***M*** UAVs navigating in an outdoor environment, and ***Ni*** is the number of features observed by the ***i***[***th***] UAV at time $t=k$. Our Airborne C-VSLAM algorithm will run centrally at the ground station and communicates the positions and the global map to each UAV as follows:

At $t=0$ the UAVs positions, velocities and orientations are known as well as the covariance matrices. During navigation, each UAV_i $i=1,\ldots,$***Ni*** observe a set of features locally and transmit information to the ground station. All these features can be categorised into three types (Fig.3):

Type1: feature re-observed by the same UAV_i.
Type2: feature re-observed by other UAV_j and $j \neq i$.
Type3: new feature observed for the first time (Not observed by any of the UAVs UAV_i $i=1,\ldots,$ ***Ni***.

Features of type1 and 2 will be used to update the map and the UAVs states (eq.15-18), whereas features of type 3 will be initialized and added to the map using the inverse model of observation [18]. When a new feature is observed by more than one UAV, then it will be initialized more accurately (red feature in Fig.3). Below are the main steps of the C-VSLAM algorithm:

- ***Initialization:***

$$U_0 = [U_{uav1}(0),\ldots,U_{uavM}(0)]^T$$
$$X_0 = [X_{uav1}(0),\ldots,X_{uavM}(0)]^T$$
$$U_0 = [U_{uav1}(0),\ldots,U_{uavM}(0)]^T$$
$$P_0 = diag([P_{uav1}(0),\ldots.,P_{uavM}(0)])$$
$$Q = diag([Q_{uav1},\ldots,Q_{uavM}])$$
$$R = I_{4\times4}$$

- ***Prediction***

$\hat{X}_{k+1/k} = f(\hat{X}_{k/k}, U_k)$ ***%State prediction using process model***

$P_{k+1/k} = F_k P_{k/k} F_k^T + \Gamma_k Q_k \Gamma^T{}_k$ ***% Covariance prediction***

- ***Update***

$\hat{y}_k = H_k X_{k/k-1}$ ***% predicted measure***

$$y_k = [\cdots \quad y_k^{i,j} \quad \cdots] = \begin{bmatrix} \cdots & u_{left}^{i,j} & \cdots \\ \cdots & v_{left}^{i,j} & \cdots \\ \cdots & u_{right}^{i,j} & \cdots \\ \cdots & v_{right}^{i,j} & \cdots \end{bmatrix}$$ ***%coordinates of the j***[***th***] ***feature observed by the i***[***th***] ***UAV***

- ***For i=1 to M*** ***%number of UAVs***
  - ***For j=1 to Ni*** ***%number of feature observed by UAVi***
  - ***Find correspondence between*** $y_k^{i,j}$ ***and*** $\hat{y}_k$
  - ***If correspondence is found***
    - $$K_k = P_{k/k-1} H_k (H_k P_{k/k-1} H^T{}_k + R_k)^{-1} \quad (15)$$
    - $$\hat{X}_{k/k} = \hat{X}_{k/k-1} + K_k (y_k^{i,j} - \hat{y}_k^l) \quad (16)$$
    - $$\Lambda_{k/k} = \begin{bmatrix} P_{k/k-1} - \gamma^2 I & -P_{k/k-1} H_k^T \\ -H_k P_{k/k-1} & H_k P_{k/k-1} H_k^T + R \end{bmatrix} \quad (17)$$
    - $$P_{k/k} = P_{k/k-1} - P_{k/k-1} [-I \quad H_k^T] \Lambda_{K/K}^{-1} \begin{bmatrix} -I \\ H_k \end{bmatrix} P_{k/k-1} \quad (18)$$
  - ***Else*** $y_k^{i,j}$ ***is a new feature to be added to the map using the inverse observation model***
  - ***End if***
  - ***End for***
- ***End for***

- ***Initialize the new features in the map***

C-VSLAM algorithm

One key requirement for SLAM to work well is feature re-observation as it improves both feature location estimates in the map and the vehicle location estimates. The latter is due to the statistical correlations between the environment features and the vehicle model.

Based on re-observation of features, one element that makes the VSLAM as a solution for long term navigation is the loop closing detection (re-visiting the same area), which is necessary to improve the consistency of the NH∞ VSLAM as shown in [18]. In the cooperative multiple UAV case, the consistency of the NH∞ SLAM is improved when a loop closing is detected and when a UAV observe features already observed by one or more cooperating UAVs. Furthermore, when a new feature is observed by more than two cameras, on each UAV, then the initialisation of that feature in the global map is more accurate.

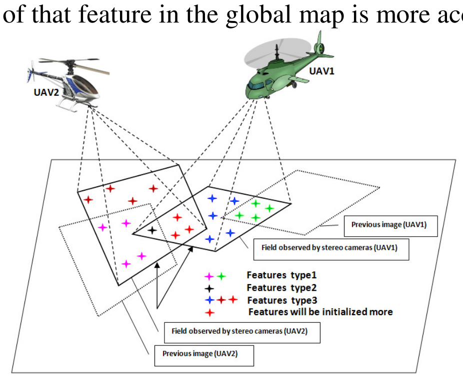
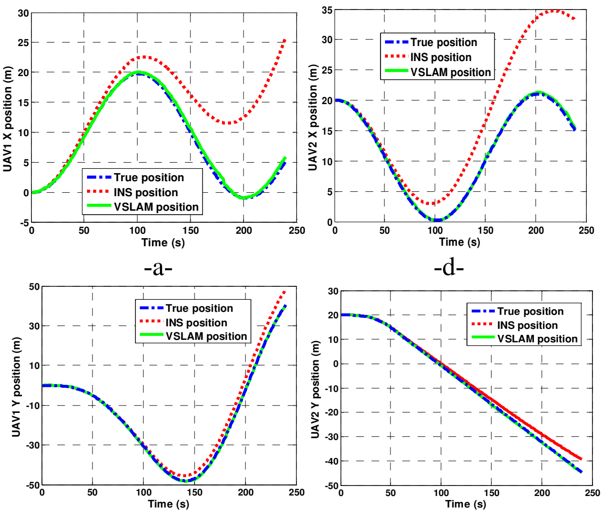


Fig.3 Features in C-VSLAM algorithm

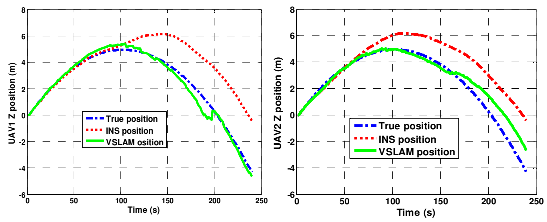
4. Simulation results

In this section, we present some results of the multiple vehicles VSLAM, using two UAVs navigating in the same area. Each UAV has an inertial measurement unit (IMU) and stereo vision cameras. Simulation environment is built in a way features as automatically seen by our camera models and used in the estimation algorithm. Results on the benefit of using NH∞ VSLAM instead of EKF VSLAM are shown in the simulation here as they have been reported in [18]. The C-VSLAM algorithm is assumed to run in the ground station and communicates with each UAV.



-a- -d-

-b- -e-



-c- -f-

Fig.4 UAVs positions, left XYZ position of UAV1 in navigation frame Right XYZ position of UAV2 in navigation frame

Fig.4 shows the simulation results of the Multiple UAV visual SLAM. Curves in the left (right) side presents the position of the UAV1 (UAV2) in the x, y and z axes. As can be seen, x position (Fig.4 a, d) and y position (Fig.4 b, e) are estimated with significant accuracy. This can be explained by the fact that cameras or stereo vision system can provide precise bearing information of the environment. This is not completely the case for the range information where the stereo vision system provides less accurate Z position as shown in Fig.4 c,f. On the above figures, we can also observe the effect of loop closing detection on UAV1 ***t=200s***, as well as the precision improvement obtained when UAV2 visits features already visited by the UAV1 at ***t1=80s*** and ***t2=150s.***

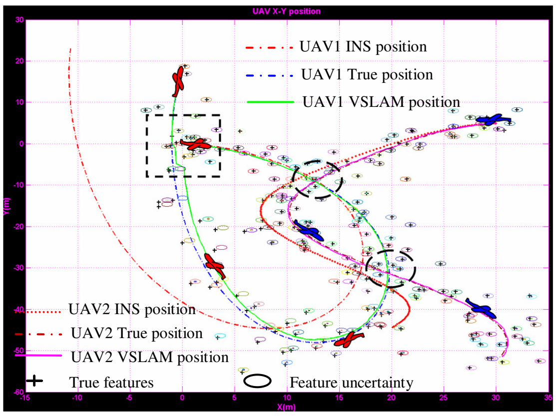


Fig.5 UAV1 and UAV2 True, INS and corrected position

Fig.5 shows the trajectories of the two UAVs in the x and y axes. While UAV1 (Red) closes its loop at ***t=200s***, (dashed square), UAV2 (Blue) does not make any loop closing but it visits many features already visited by UAV1 (dashed ellipses).

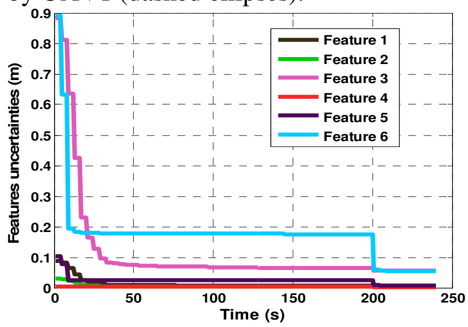


Fig.6 Features uncertainties

Fig.6 presents the evolution of the uncertainties for six features from the global map. As shown, the uncertainty of each feature decreases with time. At ***t=200s*** a significant decrease of the uncertainty is observed and this is justified by the loop closing detection, which improves the consistency of the estimator at that time.

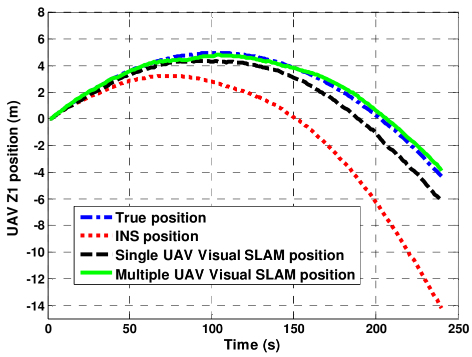


Fig.7 UAV Z estimation single UAV SLAM vs multiple UAV SLAM

Fig.7 shows a comparison between the single and multiple UAV VSLAM. As can be seen, the estimation of the UAV1 Z-position with a single VSLAM, even if it still much better than the INS position, leads to an increasing error with time. This will lead to a false position if no loop closure is detected. On the other hand, the estimation of the UAV1 Z-position with cooperative multiple VSLAM provides more accurate position. This can be explained by the fact that in the multiple VSLAM, UAV1 localizes itself based on features already visited by UAV2 (more accurate map).

Conclusions

In this paper, we proposed a robust approach to solve the cooperative multiple airborne VSLAM problem. The proposed architecture is based on an IMU/Stereo cameras system embedded on each UAV. The Nonlinear $H\infty$ filter is used and extended to multiple UAV case. The obtained results are acceptable and show more accuracy in the vehicle and map feature estimates for the cooperative multiple UAV VSLAM than for the single UAV VSLAM.

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