

Cooperative Sensor Fault Recovery in Multi-UAV Systems

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Abstract— This paper presents the design and experimental validation of a Fault Detection, Identification and Recovery (FDIR) system intended for multi-UAV applications. The system exploits the information provided by internal position, attitude and visual sensors onboard the UAVs of the fleet for detecting faults in the measurements of the position and attitude sensors of any of the member vehicles. Considering the observations provided by two or more UAVs in a cooperative way, it is possible to identify the source of the fault, but also implement a Cooperative Virtual Sensor (CVS) which provides a redundant position and velocity estimation of the faulty UAV that can be used for replacing its internal sensor. The vision-based FDIR system has been validated experimentally with quadrotors in an indoor testbed. In particular, fault detection and identification has been evaluated injecting a fault pattern offline on the position measurements, while the CVS has been applied in real time for the recovery phase.

I. INTRODUCTION

Safety and reliability become a critical issue in those tasks or applications carried out by multiple Unmanned Aerial Vehicles (UAVs) flying closely between them. Any fault on the internal position or attitude sensors of a UAV may cause deviations in its desired position or trajectory, and potentially, the collision of the affected UAV against other vehicle. Some representative examples involving close operations between two or more UAVs include autonomous aerial refueling [1], cooperative aerial transportation [2], or formation flights [3]. Having some method for detecting unexpected deviations in the normal operation of the multi-UAV system would then be useful for reducing the probability of accidents [4][5], and thus, the associated time and cost for repairing or replacing the affected vehicles. In this sense, if the UAVs of the fleet are capable to perceive partially the state of the other vehicles, then it would be possible to provide fault tolerance without requiring any addition vehicles, just exploiting the sensors onboard each UAV.

Most Fault Detection and Identification (FDI) methods for single UAV case that appear in literature try to diagnose faults based on the redundancy of some mathematical description of system dynamics and sensors onboard UAV. Model-based Component Level-FDI has been applied to fixed wing UAVs [6] and to unmanned helicopters [7][8][9]. On the other hand, Cooperative FDI makes use of all the sensors available in the multi-UAV fleet for detecting the faults in any member of the team. The usual approach is that each UAV estimates its own state and broadcast it to the rest of fleet through the communications channel [10]. What has not been thoroughly explored is the use of the sensors onboard the other vehicles of the fleet for detecting faults in an autonomous vehicle,

which requires sensing the state of a vehicle from the other team components, using for example visual or range sensors. Visual tracking with cameras onboard a pair of quadrotors is considered in [11] for estimating the position of a ground vehicle. If the vision-based position estimation is intended to UAV control, then it is convenient to analyze the influence of typical perturbations such like delay, noise, outliers or packet loss over the position-trajectory controller performance [18].

Cooperative FDI with UAVs has been researched on [12], where the position of a UAV relative to another UAV is estimated from the images that both take from the same scene, using homography-based techniques for this purpose. Visual tracking is used in [13] for estimating the position of a ground robot from a fixed-wing UAV, sending this estimation to the ground robot as external position for FDI. Virtual Sensors [14] are software modules which utilize measurable signals in order to reconstruct a signal of interest, which may be useful in replacing physical sensors, reducing hardware redundancy and acquisition cost. Nonlinear Virtual Sensors in aerospace applications have been documented in [15][16][17], although they have primarily been applied to single aircraft problems.

This paper is focused on the design and implementation of a FDIR system with quadrotors that exploits visual sensors onboard the UAVs for three tasks: detecting position and attitude sensor faults, identifying which is the affected UAV, and implementing a Cooperative Virtual Sensor (CVS) for replacing the affected position sensor. Two case studies are distinguished in the FDI process depending on if the UAVs that perform these tasks are reliable or not. The developed system has been experimentally validated in an indoor testbed with three quadrotors, although the proposed methods can be applied for an arbitrary number of UAVs.

The paper is organized as follows. Section II describes the problem of position sensor fault detection, identification and recovery using the information provided by visual sensors onboard UAVs. Section III covers the design of the FDIR system, which comprises the Cooperative Virtual Sensor (CVS), the Fault Detection and Identification methods and strategies, and the recovery part. The implementation of the multi-UAV FDIR system developed with quadrotors is detailed in Section IV, while Section V presents the results of the experiments carried out in an indoor testbed. Finally, the conclusions of this work can be found on Section VI.

II. COOPERATIVE MULTI-UAV FDIR

As there is a large variety of sensors and solutions for the localization problem, it is difficult to provide a general case explanation of all the possible situations where a sensor fault is involved. Since GPS is widely used for UAV localization, the case of GPS fault is considered as illustrative example. Figure 1 shows a scenario consisting in three quadrotors executing independent tasks. The field of view of two UAVs

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has been represented too. As seen in the upper part of the figure, the Red quadrotor, acting as target UAV, enters into a zone without GPS visibility. Using model-based fault detection methods, it could be possible for the Red quadrotor to notice that its own GPS sensor is gone, so it has no way to navigate through that area. In that moment, it sends a help request message to the rest of UAVs of the fleet. In the lower part of Figure 1, Yellow and Green quadrotors have arrived to the limits of the area and start acting as observers, visually tracking target quadrotor. Every observer will send to the target a data packet containing the position and attitude of the observer and the position on its image plane of target UAV. With this information target UAV will be able to estimate its own position and use it for its control.

From now on, it will be called target UAV to the vehicle that is under observation, and observers to the UAVs that are visually tracking the target. Any of the vehicles can be either target or observer. Note that internal position sensor of target UAV or any of the observer UAVs may or may not be working properly, what has to be solved during the fault detection phase in a cooperative way.

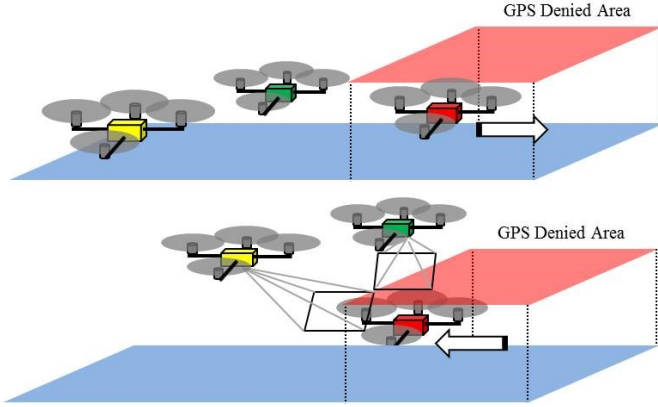


Figure 1. Fault detection and recovery example. (a) Target UAV (red quadrotor) enters in a GPS denied area. Once GPS signal loss is internally detected, target request help from observers. (b) Green and yellow quadrotors start acting as observers visually tracking target and sending their observations for target localization and recovery.

III. FDIR SYSTEM DESIGN

A. Cooperative Virtual Sensor (CVS)

Consider a system with one target UAV and two observers used simultaneously to estimate directly the 3D position of the target, creating an instance of the CVS. In normal conditions with no faults, the estimation provided by the observers should be quite similar to the estimation given by target sensor. If the distance between them exceeds a defined threshold, then a fault is detected, although it is not possible to ensure if it is associated to target or observers.

In general, two methods can be used to estimate target position from the measurements provided by the observers: geometrically considering the closest point between the projection rays, or using a non-linear probabilistic estimator as the Extended Kalman Filter (EKF) or the Unscented Kalman Filter (UKF). In the geometric method, the projection rays obtained from the projection points of target on the image plane of the observers should ideally intersect in a point corresponding to target's position. If the projection rays do not

cross, it is necessary to consider the closest points between these two lines. Intuitively, the distance between these points gives an idea of how reliable the estimation is. Furthermore, some errors in position or orientation measurements of observers' sensors will cause the distance between these two points to increase, which can be exploited to detect faults on observers. This has been represented in Figure 2. The left side represents the ideal case in which the projection rays cross exactly in the target, while in the right side a fault on Observer-1 position sensor makes the projection ray to diverge, taking the midpoint between the closest points between both projection rays as estimated position.

Let denote by P_{ik} and P_{jk} the closest points between the projection rays from observers i and j to target k . Target position given by internal sensor and estimated by the CVS will be represented by r_k and \hat{r}_k respectively. Finally, D_{ijk}^{th} will be the fault detection threshold for observers i and j sensors when they are focused on target k , while d_{ijk}^{th} will be the fault detection threshold for target position sensors. Both thresholds will be defined taking into account the relative position between target and observers. Then, the following three situations are considered for the peer-observer fault detection case:

- If $\|P_{ik} - P_{jk}\| \geq D_{ijk}^{th}$ then a fault is detected in the position and/or attitude sensors of observer UAV- i or in observer UAV- j when they are focused on target UAV- k .
- If $\|P_{ik} - P_{jk}\| < D_{ijk}^{th}$ AND $\|\hat{r}_k - r_k\| \geq d_{ijk}^{th}$ then a fault is detected on target UAV- k position sensor when it is observer by UAV- i and UAV- j .
- If $\|P_{ik} - P_{jk}\| < D_{ijk}^{th}$ AND $\|\hat{r}_k - r_k\| < d_{ijk}^{th}$ then no fault is detected.

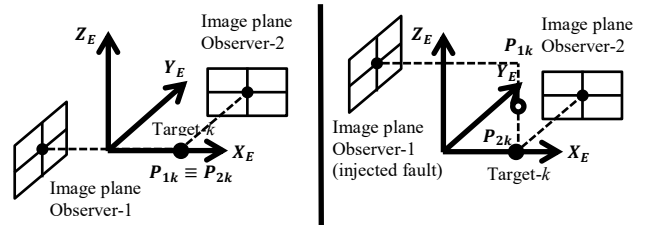


Figure 2. Ideal case of projection ray intersection on target (left) and estimation as midpoint between the closest points of the projection rays when there is a fault on Observer-1 (right).

In the general case with N observers ($N \geq 3$), there are $M = N \cdot (N - 1) / 2$ pairs of observers that can provide a 3D estimation of target UAV position using the geometric method. As in the previous case with two observers, fault detection on observers' sensors should be done previously to fault detection on target sensor. Now, with three or more pairs of observers it is possible to identify the particular UAV affected by the fault. Consider a situation with four UAVs, where UAVs 1, 2 and 3 act as observers and UAV-4 as target. Imagine that $\|P_{14} - P_{24}\| \geq D_{124}^{th}$ and therefore a fault is detected on observers' pair 1-2. In order to identify which is the affected observer, the other two possible combinations are evaluated, obtaining that $\|P_{14} - P_{34}\| \geq D_{134}^{th}$ and $\|P_{24} - P_{34}\| < D_{234}^{th}$, which implies that the faulty should be UAV-1.

B. Fault Detection and Identification Methods

It is convenient to distinguish two case studies depending if the sensors of the observers are reliable or not. The worst case is that in which it is not possible to assume if the fault is in the target or in any of the observers, although depending on the particular application and features of the UAVs it may be possible to have an initial guess of where the fault is located. This paper proposes methods for detecting faults in both cases, assuming that the tracking algorithm is reliable.

Let denote as \vec{r}_{int} and \vec{r}_{CVS} to the position estimation of the target UAV given by its internal (and possible faulty) sensors and by the CVS. Assuming that CVS estimation is reliable, that is, the internal position and orientation sensors of the observers are not affected by faults, then both estimations should be quite close in normal conditions. The simplest way of detecting a fault on target position sensors is evaluating the distance between both estimations with respect to a threshold:

$$\|\vec{r}_{int} - \vec{r}_{CVS}\| > d_{th} \quad (1)$$

This criterion can be extended to detect faults on particular axes:

$$\begin{aligned} \text{Fault on } X - \text{axis: } \|x_{int} - x_{CVS}\| &> d_{th,X} \\ \text{Fault on } Y - \text{axis: } \|y_{int} - y_{CVS}\| &> d_{th,Y} \\ \text{Fault on } Z - \text{axis: } \|z_{int} - z_{CVS}\| &> d_{th,Z} \end{aligned} \quad (2)$$

The effectiveness of such a simple method relies on the selection of the appropriate detection threshold, taking into account that small values may introduce frequent false positives, while high distances imply higher amplitudes of errors and thus lower reaction times. If the observation conditions (relative position between target and observers, number of observers) remain constant during the FDIR phase, then the following constant threshold is well suited:

$$d_{th} = K \cdot e_n \quad K \sim 2, 3 \quad (3)$$

where K is the tolerance constant, and e_n is the nominal estimation error in normal observation conditions without sensor faults. The best observation conditions are those in which the target and the observers move jointly with a zero relative speed between them, and the separation angles between the projection rays of the target on the image plane close to 90 deg [19]. Note that if the fault detection phase is based on the CVS, then at least two observers are necessary.

The FDI process can be performed without computing the 3-D CVS estimation, just evaluating the expected and measured position of the target on the image plane of the observer. Let $\vec{X}_m^{ik} = [x_m^{ik} \ y_m^{ik}]^T$ be the measured centroid of target UAV- k projected on the image plane of observer UAV- i , and $\vec{X}_e^{ik} = [x_e^{ik} \ y_e^{ik}]^T$ the expected projection point computed from target position and from camera pose, where any of these measurements may be subject to failure. If \tilde{d}_{ik} is the expected distance between observer UAV- i and target UAV- k and f is the focal length of the camera, then the transversal projection error is defined:

$$\vec{\varepsilon}_{ik} = \left[\tilde{d}_{ik} \cdot \frac{x_m^{ik} - x_e^{ik}}{f} \quad \tilde{d}_{ik} \cdot \frac{y_m^{ik} - y_e^{ik}}{f} \right]^T \quad (4)$$

The above index can be interpreted in the following way. Consider a plane parallel to the image plane and centered on

target expected position given by its internal sensor. The measured centroid given by the tracking algorithm is projected on this plane. The error is then the difference between the expected and measured points in the XY axes of the plane.

Two relevant facts are derived from the definition of the transversal projection error. Firstly, as the expected projection point depends on camera pose measurements, any fault on the position or attitude sensors of the observer can be detected. On the other hand, position sensor faults on the direction of the projection ray from target to camera cannot be detected. However, in practice this limitation can be easily solved just changing the point of view or considering a second observer.

Let δ_{ik} be a binary variable taking value one if observer UAV- i detected a fault on target UAV- k , and zero otherwise. If the observers are properly positioned in different point of views around the target, then the identification of the fault can be done based on the following variable:

$$S_k = \sum_{\forall i \neq k} \delta_{ik} \quad (5)$$

If $S_k = 0$ then no fault is detected by any of the observers; if $S_k = N$ then a fault on target is confirmed by all observers; if $S_k = 1$ then a fault is probably located in UAV- i such that $\delta_{ik} = 1$. In other case, there might be multiple failures.

C. Position Sensor Fault Recovery

The geometric method based on ray intersection for obtaining an estimation of target UAV position can be more convenient than nonlinear Kalman filter estimators for the fault detection phase, as it is more intuitive and simple. However, if the CVS estimation is going to replace faulty position sensors for UAV control, then the second option is more suited for three main reasons. First of all, it makes possible to integrate the observations taken by an arbitrary number of UAVs in a quasi-optimal way, even these measurements are not periodic or synchronized between the observers. Note that the 3D position estimation problem using image sensors is nonlinear. Second, the definition of the state vector includes not only target UAV position, but also velocity, which cannot be obtained directly from the geometric method and can be useful for the UAV control. Finally, the state estimation provided by the Kalman filter is already filtered, reducing the influence of noise and outliers in observers measurements without requiring any additional filter. One important issue associated with the Kalman filter estimator is the initialization of the state vector. It was found during experiments that initial position estimation on state vector had to be relatively close to the real position of the target so the Kalman filter can numerically converge. This can be solved simply taking the geometric estimation for the initial guess.

In this work, an Extended Kalman Filters has been used for the estimation of the position and velocity of a visually tracked object, taking as measurements its centroid projected on the image plane of each camera. The position and orientation of the observers are taken as known parameters in the estimation. A radial and tangential distortion model for the pin-hole camera is applied over the estimated output

measurement to increase accuracy. Experimental results show that position estimation accuracy strongly depends on the relative position between the target and the observers. Uncertainty in the estimation can be minimized placing the observers around the target in such a way that projection rays orthogonal between them in the three directions of the space, maintaining a constant distance with respect the target.

IV. FDIR SYSTEM IMPLEMENTATION

This section describes some implementation details related with the FDIR system developed and tested with quadrotors in the CATEC indoor testbed. This testbed is equipped with a Vicon Motion Capture System that provides under-centimeter accuracy in the position and orientation of ground and aerial vehicles moving in a 15 x 15 x 5 meters volume.

A. Aerial Platform

Three Hummingbird quadrotors (two observers and one target) from Ascending Technologies were employed for the FDIR experiments. Observers were equipped with a tracking module system consisting in an Odroid U3 computer board, a Logitech C525 webcam and a USB-N53 adapter dual-band wireless-N600 from FAST networking solutions. Figure 3 shows one of the quadrotors equipped with the tracking module and the three UAVs employed in the experiments in a synthetic urban environment. The target was endowed with a blue color marker in contrast with the colors of the floor so the tracking algorithm can easily detect it.



Figure 3. Hummingbird quadrotor with equipped tracking module (left) and the three quadrotors employed in the experiment in a synthetic urban environment (right). The target in the middle is endowed with a blue marker.

The tracking modules contain two software modules for two types of experiments. The first one is the data acquisition program which captures and stores the sequence of images and the Vicon measurements for offline data analysis and processing. The second program is the tracking algorithm for the real-time execution of the FDIR experiments. For every frame captured by the cameras where the target is detected by the tracking algorithm, a data packet containing the position of the target on the image plane and camera pose is sent to the CVS and FDIR modules for updating the fault detection report and the vision-based position estimation of the target.

B. Tracking Algorithm

A modified version of the CAMShift algorithm [20][21] was employed for obtaining the centroid of the target (or more precisely the centroid of the color marker attached to the target) on the image plane of the cameras. This algorithm was selected due to its low computation requirements in time and memory, and for its robustness against blurring, outliers,

noise and changes in the illumination conditions. Its main limitation is that the color of the tracked marker should have sufficient contrast with the background.

The basic implementation of the algorithm contained in the OpenCV library is not able to manage when the object selected as target goes out of the field of view of the camera or is lost due to occlusions. For that reason, tracking loss detection and object redetection capabilities were introduced, using geometric information related to the tracked marker such as expected dimensions or aspect ratio for this purpose. A model of the marker containing its color distribution, saturation and brightness thresholds and other geometric parameters is taken as input by the program embedded in the Odroid. This model is generated from a picture of the color marker obtained in the normal observation conditions. The computational time when executed in the Odroid U3 board is around 40-50 ms for a 640x480 pixels resolution, including the image capture from camera and image processing times.

C. Functional Entities and Data Flow

The FDIR experiments carried out in the CATEC testbed involved the resources in Figure 4. Two observers (UAV-1 and UAV-2) are equipped with a tracking module that generates observations containing the projection of the target (UAV-3) on the respective image plane, along with the current position and orientation of the cameras and a global time stamp for data synchronization. These measurements are sent through a wireless network to the CVS and FDIR modules. The computational time associated to these modules is negligible with respect the image processing time. All the UAVs take as input the position references sent by the UAV Control Centre through the CATEC Network. A number of ROS (Robot Operating System) nodes control the different phases of the experiment (take-off and landing, trajectory tracking, UAVs positioning, target tracking and target recovery). The CVS estimation is introduced in the target recovery node replacing the internal position sensor.

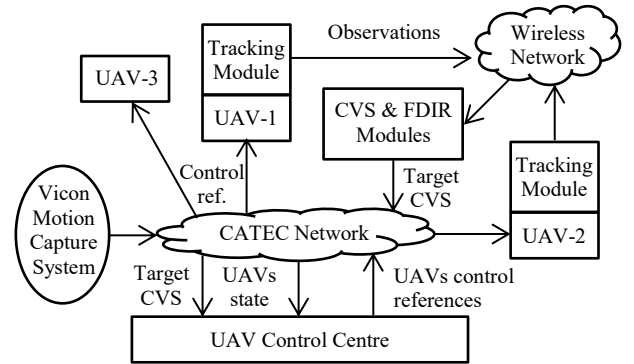


Figure 4. Functional entities and data flow involved in the implementation of the FDIR system with three quadrotors in the CATEC testbed.

D. Target Controller in the Recovery Phase

For safety and simplicity reasons in the development and experimental validation of the FDIR system, the application of the CVS estimation for controlling target UAV during the recovery phase was implemented according to the scheme

shown in Figure 5. As seen, the quadrotor takes the Vicon measurements in the inner control loop as position feedback. Instead of modifying the software of the controller, the idea is to synthesize a position reference in such a way that Vicon measurements are subtracted from the outside, introducing the CVS estimation with negative sign. In practice, this is the same as using Vicon but injecting the CVS estimation error in the control loop. However, the estimation error was kept monitored during the recovery experiments to prevent using the CVS if it exceeds a 0.15 m threshold.

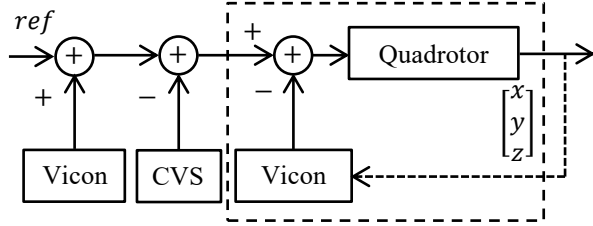


Figure 5. Control scheme for replacing the Vicon system in the control loop with the CVS during the recovery phase in the experiments.

V. EXPERIMENTAL RESULTS

This section presents experimental results that validate the proposed fault detection and identification methods (offline fault injection) and the real-time application of the CVS for the recovery phase of a target quadrotor when it is visually tracked by two observer quadrotors.

A. Trajectories and Phases in FDIR

The 3D trajectories followed by target and both observers since the fault detection phase starts until all the quadrotors have landed has been represented in Figure 6, while target position ground truth and CVS estimation in XYZ axes are shown in Figure 7. The observation positions in the XYZ axes, considering target position as origin, were $[-1, 1, 1]^T$ and $[1, 1, 1]^T$ for both observers. The observers have been positioned in such a way that the separation angles between the projection rays from the target to the cameras are close to 90 deg (orthogonal configuration), so the uncertainty in the estimation is minimized [19].

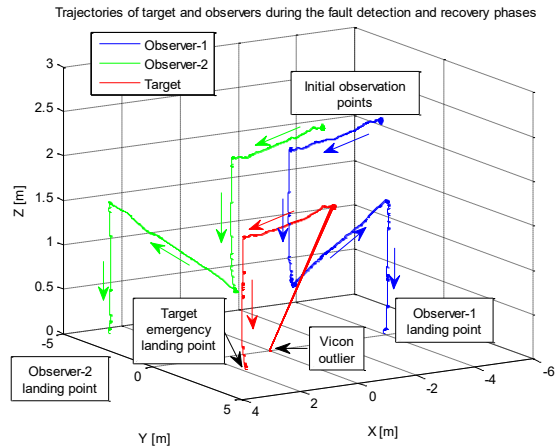


Figure 6. Trajectories followed by the target and both observers during the FDIR phases, from initial observation points to landing points.

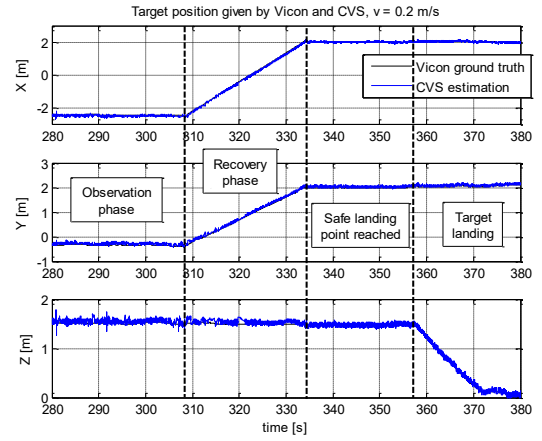


Figure 7. Target position ground truth given by Vicon (black) and CVS estimation (blue) during the FDIR phases. Target speed was set to 0.2 m/s

Figure 8 shows the results of the fault detection phase for one of the observers when several additive failures are injected in target quadrotor in the XYZ axes at different time instants. The projection error detected by both observers goes above the detection threshold, thus triggering the presence of a fault. Results for second observer are not shown as they are similar. Therefore, it can be concluded that the fault is in the position sensors of the target.

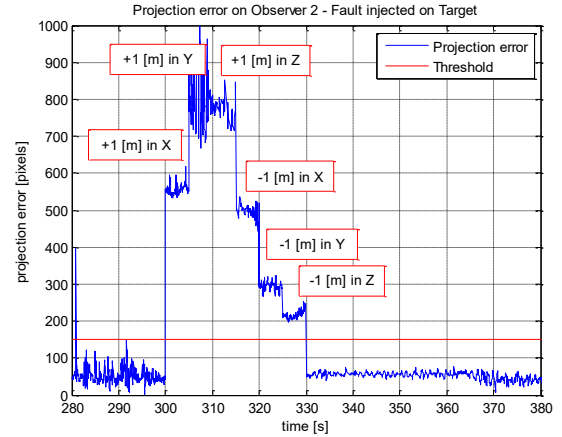


Figure 8. Transversal projection error (blue) and detection threshold (red) when a fault pattern is injected on target position measurements.

For the target recovery phase, the internal position sensor of target UAV is replaced by the CVS estimation according to the scheme shown on Figure 5. The configuration for this experiment is the same as in the previous case, changing only target speed to 0.1 m/s. Figure 9 shows CVS estimation error, taking Vicon as ground truth, while Figure 10 and Figure 11 show respectively target velocity and speed given by the EKF (blue) and computed by differentiation of Vicon position with respect time (black).

VI. CONCLUSION

This paper has presented the design and experimental validation of a FDIR system for multi-UAV applications. The system takes advantage of the sensors onboard the UAVs to build a cooperative virtual sensor that estimates the position of another UAV that can be used for fault detection. When

there is a fault in the positioning sensors or a temporary loss (i.e. GPS loss), the CVS can be used to guide the UAV with the faulty sensor to a safe state. The experimental results obtained in an indoor testbed validate the system design.

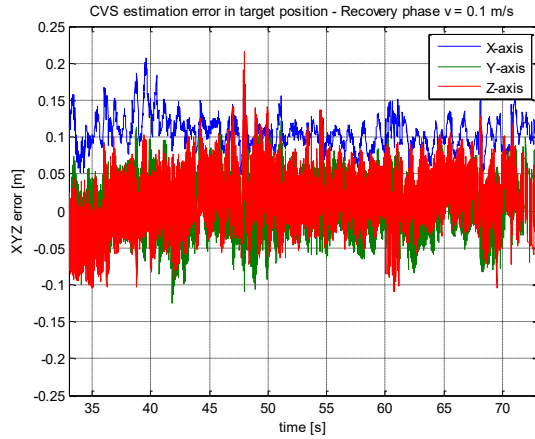


Figure 9. Target XYZ position estimation error during the recovery phase.

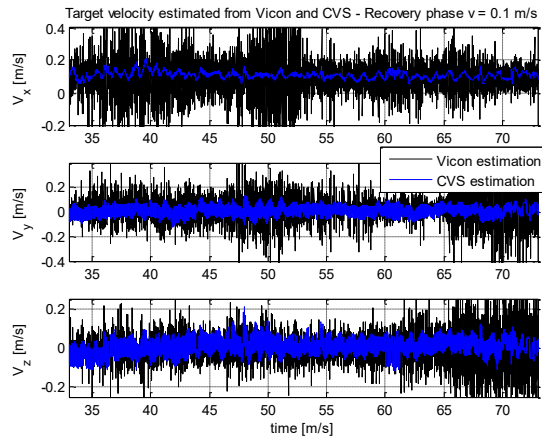


Figure 10. Target XYZ velocity estimation computed from Vicon position differentiation (black) and given by the EKF implementing the CVS (blue).

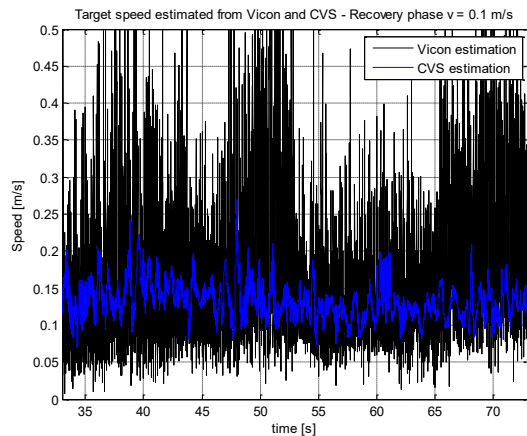


Figure 11. Target speed estimation computed from Vicon position differentiation (black) and given by the EKF implementing the CVS (blue).

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