



# Multiple Fault Detection and Isolation in Target Tracking Using Liner Prediction Techniques

Wasi Ullah<sup>1</sup>, M. Kamran Shereen<sup>2</sup>, M. Iftikhar Khan<sup>3</sup>, Naeem Khan<sup>4</sup>

**Abstract**—This paper proposes schemes for fault detection and isolation in a multi-fault setting. Now-a-days, sensor fault and failure are important issue in various wireless sensor networks. This works suggests a few algorithms based on simple phenomenon of data fusion. Initially, a mutual consensus has been developed among followers (e.g. UAVs in this case) who are tracking the same target. Having known the followers relative positions w.r.t. target, a median is computed by each follower. This median is then shared with neighbours to compare with their estimated values about the target position. If estimation is beyond the defined limits, the follower (sensor) is detected as faulty otherwise healthy. Three different types of induced faults are discussed here as: follower – target or line of communication fault, follower – follower or communication with neighbour fault and simultaneously these two faults. A generalized scenario with definit formation of these followers has been considered to elaborate these faults.

**Keywords**— FDI, Data Fusion, Sensor Faults, Target Tracking.

## I. INTRODUCTION

The importance of autonomy of vehicles is increasing every day, as the world moving toward complexity. Consider that we observe in a daily routine if a driver drives a car and face an obstacle during mission at hand they can easily avoid the obstacle in front of him but in case of UAVs this process is quite complex. The UAVs have some method to sense the surrounding obstacles and take the information and identify the obstacle. Then they take control decision on the basis of that information to avoid the obstacle. Each UAV is likely programmed with its desired destination but then is required to follow the input to travel from its current to its destination position. For a human operator these tasks are relatively simple as compared to UAVs. The majority of automated tasks have one key component in common, that there exists a target tracking path available to the UAVs that allows it to carry out its mission. Target tracking Path planning underpins the degree of autonomy that UAVs can achieve. Without proper target tracking path information it is impossible for UAVs to be expected to be able to carry out its mission as it simply does not know how it should be moving. The starting point for target tracking during any mission is the reference path for target tracking information that the (UAVs) needs to successfully complete mission.

One important task of a typical sensor network is to detect and report the locations of targets e.g. Tanks, land mines, etc, in the presence of faulty sensor measurements [5].

Multi-UAV target tracking is the same as multi sensor target tracking in spirit which already has been a popular topic in the literature, e.g. [13]. Among many target tracking schemes, we are predominantly attracted in decentralized target tracking combined with fault detection schemes due to their flexibility, cost effectiveness and robustness. Regarding decentralized target tracking schemes, one can easily notice that the schemes employ so called consensus-type algorithms. These algorithms essentially allow each agent (sensor, UAV, etc) to assemble information from its immediate neighbours and to update its information, so that every agent agrees on the common or very similar information at the end. Depending on the final common information  $f$ , these algorithms are called average-consensus, median-consensus, or  $f$ -consensus algorithms. Several recent works propose such decentralized consensus Algorithms in Gaussian noisy environments, in which they use Kalman filter type estimation rules, e.g. [11] or low-pass or high-pass filters, e.g. [10], [14]. A large number of fault detection schemes have been proposed in the literature. Most recent applications of these schemes have been for wireless sensor networks, e.g. [6], [7], [8], [9], [12], where maximum likelihood, Bayesian, or voting approaches are taken to detect and isolate faulty sensors. In particular, we note one of the most recent works, [6], in this direction. In a typical study, the authors claim that under a mild assumption the proposed decentralized scheme is capable of almost detecting faulty sensors, even if half of the neighbouring sensors are faulty [1].

The current work resolve the above mentioned issue by developing a consensus scheme for a generalized network scenario of target tracking, where in target is tracked down by the followers. The proposed scheme guarantees accurate fault detection and isolation if there exists any faulty sensor in the network, thus assuring successful tracking of the target which is the primary objective of the generalized scenario.

## II. PROBLEM STATEMENT

The objective of this paper is to track a target in a network while maintaining a defined formation  $\mathfrak{R}$ . When all the sensors have no fault, the formation may be maintained by just keeping the distances constant w.r.t. target. However, when a sensor/UAV is unable to track the target due to any unwanted condition/s, how to track the target is the issue address in this paper.

### III. PROBLEM SCENARIO

Among the eight (04) follower UAVs, the corresponding target position estimated by  $l^{th}$  UAV is denoted by  $P_l(t)$ . It is assumed that position sensor reading follows Gaussian distribution due to which estimated target position information deviates from the true target position  $P(t)$ . The deviation is standard deviation  $\sigma$  relative to the true target position  $P(t)$ . Each UAV shares its information with all other UAVs (neighbours) within its sensor range. It is because each UAV should act according to the very similar information to keep the defined formation  $\mathfrak{R}$  throughout the mission. Let the number of faulty sensors  $f$  in the network is less than half of the total sensors in network i.e.  $f < n/2$  where  $n$  is the total number of sensors in the network. It is assumed that for the  $l^{th}$  UAV to track the target, it must first estimate the target position  $a_l(t + \Delta t)$ . Once the  $l^{th}$  UAV has this information it can easily change its current position  $b_l(t)$  to  $b_l(t + \Delta t)$  to maintain the initial formation  $\mathfrak{R}$  relative to target position by using

$$b_l(t + \Delta t) = a_l(t + \Delta t) + b_l(0) - a_l(0)$$

Where

$b_l(t + \Delta t)$  is  $l^{th}$  UAV position at time  $t + \Delta t$ ,  $a_l(t + \Delta t)$  is target position at time  $(t + \Delta t)$ ,  $b_l(0)$  is  $l^{th}$  UAV initial position at time  $t=0$ , and  $a_l(0)$  is target initial position at time  $t=0$ .

### IV. PROPOSED ALGORITHMS

The proposed fault tolerant scheme consists of three algorithms:

1. Data fusion algorithm [1,10]
2. Line Of Communication FDI algorithm [10]
3. Communication with Neighbour fault detection algorithm

The LOC is a link between an UAV and target through which the UAV measure target position. On the other side, a CN is a medium two between UAVs through which they share their target position information with each other.

#### A) Data Fusion Algorithm

The data fusion algorithm is employed by each UAV to update target position information and then change its position accordingly. The equation that summarizes data fusion algorithm [10] is

$$a_l(T) = (1 - \beta)a_l(T-1) + \sum_{m \in M_l^r} [c_{lm}(T-r)p_m(T-r)] \quad (1)$$

Where  $a_l$  is estimated target position by  $l^{th}$  UAV,  $b_l$  is  $l^{th}$  UAV position information,  $r$  is the number of links with neighbors,  $P_m$  is  $m^{th}$  UAV sensor information and  $M_l^r$  is the set of  $l^{th}$  UAV and its  $r$ -neighbors which can be reached from

$l^{th}$  UAV through  $r$  links. The number of faulty sensors  $f$  in the set  $M_l^r$  must be such that  $f < r/2$  and  $C_{lm}$  is [1]

$$c_{lm}(T-r) = \frac{\beta \sigma^{-\gamma} |p_l(T-r) - p_j(T-r)|}{\sum_{m \in M_l^r} \sigma^{-\gamma} |p_l(T-r) - p_j(T-r)|} \quad (2)$$

In the above equation,  $\beta$  and  $\gamma$  are constant parameters. Its values are  $0 < \beta < 1$  and  $\gamma > 0$ , where  $P_l$  is the median of target position information of the  $l^{th}$  UAV sensor information and its neighbors readings. Initially when sensors are not diagnosed for fault yet, let all the sensors are healthy and non of the sensor is faulty thus making  $r$  equal to  $l$  i.e.  $r=l$ .

#### B) LOC Fault Detection and Isolation Algorithm

The above discussed data fusion algorithm is employed by UAV to estimate the target position information, using this information, an UAV estimates its new position and move to that new position but at the same time the LOC (Line Of Communication) fault detection and isolation algorithm also operates in order to detect for faulty sensors in the network and isolate them from the network. This scheme follow two steps: First, it finds the global median of target position from the estimated target position (s) information of the UAVs belonging to the set  $M_l^r$  over  $l^{th}$  UAV within a fixed tolerance; Secondly, that global median is then propagated to the UAVs belonging to the set  $M_l^r$  in order to determine faulty UAVs (those UAVs which have deviations with the global median beyond the defined tolerance) and non-faulty UAVs.

In the first step of LOC FDI algorithm, the set of UAVs is  $M_l^r$  which is used to find the global median of target position information by collecting the target position information from the UAVs of set  $M_l^r$ , must satisfy the condition of  $f < n/2$  i.e. the number of faulty sensors  $f$  in the set  $M_l^r$  must be less than half of the total sensors  $n$  in that set. It is because one needs  $f+1$  similar information i.e.  $|p_l - p_m| \leq 2\sigma$  in order to find the correct global median of target position information. If the set  $M_l^r$  does not satisfy the condition  $f < n/2$  or the set  $M_l^r$  does not have  $f+1$  similar information then global median cannot be calculated from that set. In such case, the concept of extended neighbor is utilized i.e. extended neighbors are added to the set  $M_l^r$  and then global median is calculated. In short, any UAV requires at least three similar information in order to find true global median of target position information.

In the second step of LOC FDI algorithm, the found global median is distributed among the UAVs belonging to the set  $M_l^r$  to diagnose for faulty and healthier sensors. If the difference  $|Glo.Med - p_l|$  exceeds  $2\sigma$  the sensor is diagnosed as faulty. Once the sensor is diagnosed as faulty its

information is replaced by global median in order to prevent faulty information from entering into the data fusion algorithm thus assuring that faulty sensors are isolated from the network.

C) CN Fault Detection Algorithm

Beside data fusion algorithm and LOC FDI algorithm i.e. CN fault detection algorithm also operates to disclose CN fault in the network. CN fault is a fault in those sensors through which UAVs communicate with its neighbors. If CN fault exists between any two UAVs then these UAVs may not be able to share their target position information and global median information with each other. So detection of such fault is important in order to improve the accuracy of target tracking.

V. SIMULATION RESULTS

The above three tables show the proposed data fusion algorithm, LOC fault detection algorithm and CN fault detection algorithm respectively.

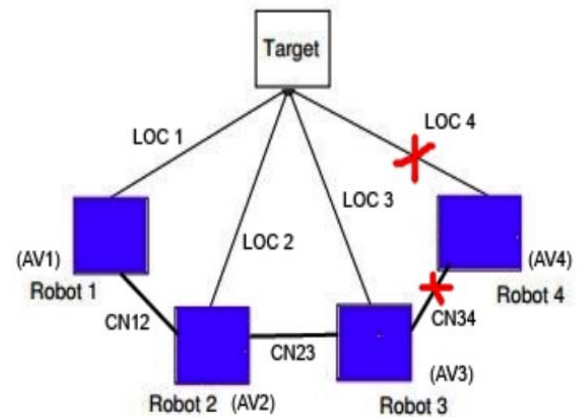


Fig 2. General Scenario with Multiple Faults

In this scenario, UAV 4 is unable to track the target, leading to the failure of mission because of faulty sensor's information about target position. The simulation results are shown for the faulty scenario (LOC and CN Fault simultaneously). Due to the employment of LOC algorithm, one can see UAV 4 is still tracking the target in the presence of sensor faults. This is due to the operation of semi-decentralized data fusion algorithm and LOC FDI algorithm which forces faulty UAVs to track the target, stay confined to the trajectory and maintains the initial distance constant throughout the mission.

It can also be confirmed that the trajectories of UAV 4 (represented by blue line) deviates from the exact path at the instant of fault occurrence in the system. Once the fault is diagnosed, the LOC-FDI algorithm causes to remove the reading of faulty UAVs/sensors from computing the global median.

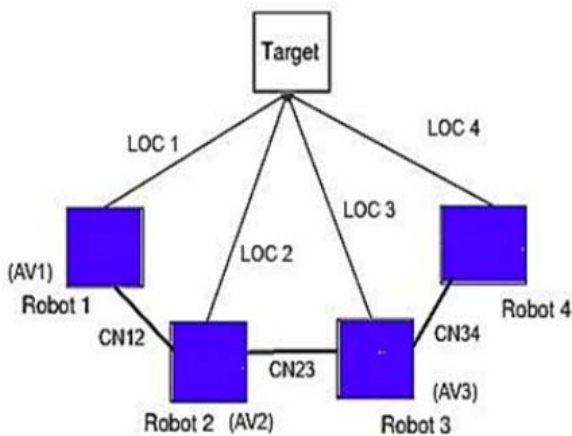


Fig 1. General Scenario

Fig. 1 represents the general scenario that has been considered to testify the proposed algorithms. In the Figure, the white box represents the target which is tracked by four UAVs represented by blue boxes. The lines between target and UAVs represent LOC links (connecting each UAV with target) through which each UAV senses the target position and track it down. The lines (among successive UAVs) represent CN links through which each UAV communicate with its neighbor sharing its own target position information. Let the target enters into a bad weather condition zone where UAV4 cannot sense the actual target position as shown in Fig. 2.

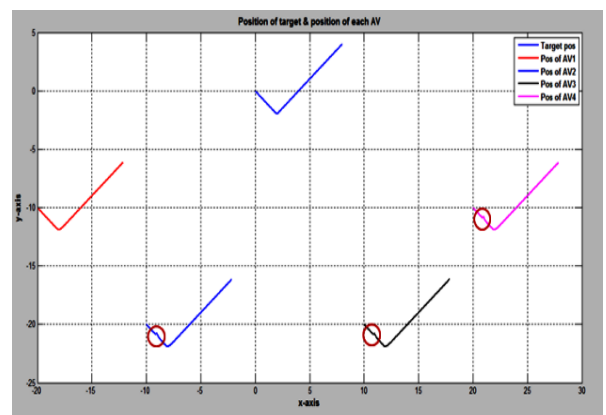


Fig 3. Trajectory with faults

Fig. 3 shows a clear picture of trajectories of the target and the follower UAVs claiming that UAV 4 is not tracking the target accurately as their sensor cannot sense the target position.

The LOC fault exists in UAV 4 whereas UAV 4 and UAV 3 have CN fault which prevents information flow between them. Since UAV 4 is suffering from LOC fault (and cannot

sense the target) and at the same time, it suffers from CN fault, hence it should not be able to track the target accurately. The simulation results in Fig. 4 clearly shows that UAV 2 is unable to track the target accurately as it is suffering from both LOC and CN faults shown by blue line below.

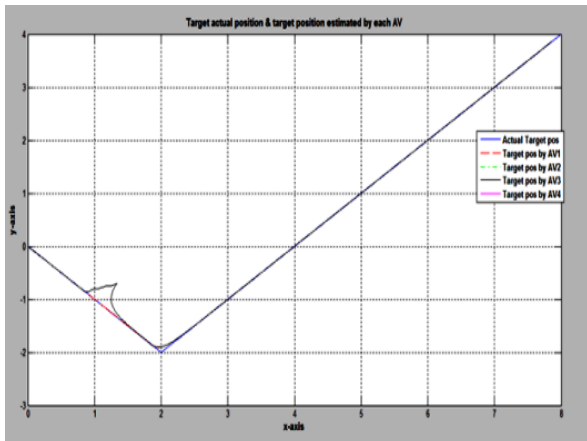


Fig 4. Trajectory with Multiple Faults

Implementing the proposed LOC and CN-FDI algorithms simultaneously have resulted in superior performance. The affected UAV 4 is tracking the target with better result as shown in Fig. 5.

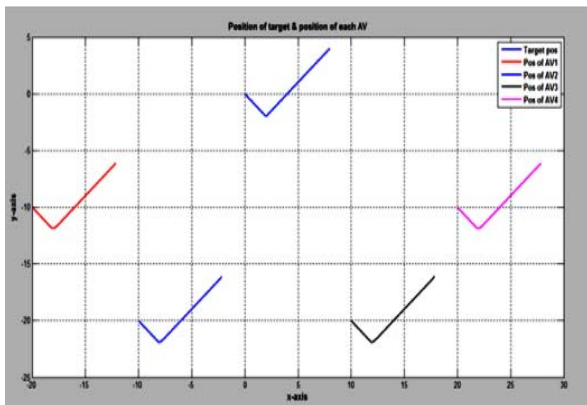


Fig 5. Trajectory with FDI Algorithms

## VI. SUMMARY

In this paper, the suggested scheme designed for multi sensor target tracking network consist of three algorithms: data fusion algorithm, LOC fault detection and isolation algorithm and CN fault detection and isolation algorithm. The main objective is finding of global median from non-faulty sensor

information using algorithm. This global median is used to find faulty and non-faulty sensors using Line-of-communication FDI algorithm and Communication-with-neighbor FDI algorithm.

## REFERENCES

- [1] Y. Kim, D. W. Gu and I. Postlewaite. Fault-tolerant cooperative Target Tracking in Distributed AV Network, IFAC 2008, Seoul Korea.
- [2] D. Smith and S. Singh. Approaches to multisensory data fusion in target tracking: a survey. IEEE Transactions on Knowledge and Data Engineering, 18(12): 1696-1710, 2006.
- [3] W. Ren, R. W. Beard and D. B. Kingston. Multiagent Kalman Consensus with Relative Uncertainty. In the proceeding of American Control Conference, Pages 1865-1870, June 2005.
- [4] J. Chen, S. Kher and A. Somani. Distributed fault detection of wireless sensor networks. In the proceeding of the wireless ADHoc Networks and Sensor Networks, Los Angeles, Sep 2006.
- [5] H. Alwi, C. Edwards and Andres Marcos. Fault reconstruction using a LPV sliding mode observer for a class of LPV systems, Journal of the Franklin Institute, 2012, 349(1) pages 510-530, June-2012
- [6] S. Grenaille, D. Henry and A. Zolghadri. A method for designing fault diagnosis filters for LPV polytopic systems. Journal of Control Science and Engineering, 1(6), pages 1-11, 2008.
- [7] B. Bhajantri Lokesh And N. Nalini, Bayesian Network Based Fault Tolerance In Distributed Sensor Networks, Journal Of Telecommunication And Information Technology, 4/2014 Pages. 44-52
- [8] X. Kuang, S. Jiao And H. Shao. Maximum Likelihood Localization Algorithm Using Wireless Sensor Network. First IEEE, International Conference On Innovative Computing, Information And Control Iccic, P 263-266
- [9] J. M. Bass, Latif-Shabgahi, G. Bennett, S. Experimental Comparison Of Voting Algorithms In Cases Of Disagreement, Proceeding Of The 23rd Euromicro Conference, Pp. 516-523, 1997
- [10] I. postlewaite, D. W Gu, Y. Kim, K. Natesan, M. Kothari, N. khan and R. Omar. A robust fault-tolerant tracking scheme, realising network enable capability, meec08, leeds uk, 2008.

**Wasi Ullah** is Lecturers at Department of Electrical Engineering UET, Peshawar

Email: engr.wasiullahkhan@gmail.com

Contact No.: 0332-974180

**M. Kamran Shereen** is Lecturers at Department of Electrical Engineering UET, Peshawar

**M. Iftikhar Khan** is Assistant Professors at Department of Electrical Engineering UET, Peshawar

**Naeem Khan** is Assistant Professors at Department of Electrical Engineering UET, Peshawar