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Research Article

Enhanced Performance of Consensus Fault-tolerant Schemes for Decentralized Unmanned Autonomous Vehicle System

Naeem Khan*, Aitzaz Ali, and Wasi Ullah

*Electrical Engineering Department, University of Engineering and Technology Peshawar, Bannu Campus, Pakistan

Abstract: This paper addresses schemes for fault detection and isolation in a semi-decentralized environment. Now-a-days, sensor fault and failure are prevalent issues in numerous wireless sensor networks. We propose a few algorithms based on simple phenomenon of data fusion. Initially, a mutual consensus has been built among followers (e.g., Unmanned Autonomous Vehicles in this case) who are tracking a combine target. Having known the followers, relative positions with respect to target, a median is computed by each follower. This median is then shared with immediate and extended neighbours to compare with their estimated values about the same target position. If estimation is beyond the prescribed limits, the follower (sensor) is diagnosed as faulty, otherwise is considered healthy. Three different types of induced faults are discussed here: (i) follower – target or line of communication fault; (ii) follower – follower or communication with neighbour fault; and (iii) simultaneously these two faults. The scenario wherein eight followers are tracking a combine target in circular fashion has been considered to elaborate these faults.

Keywords: Median, FDI, data fusion, sensor faults, target tracking

1. INTRODUCTION

In the modern era the use of sensors is increasing day by day. Sensors are very useful as they measure physical quantities and convert them into signals [1]. These signals are then observed by observers or instruments which can be processed further for controlling purposes. As the world is moving towards autonomy and sensors are the core devices to give the feature any autonomous system, autonomous research is prevailing day by day [2]. However, majority of sensors are electronic devices and are vulnerable to faults and failures. The fault/failures may be because of electronic malfunctioning, manufacturer defect or bad weather condition etc. An important issue 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 [3].

The requirements for sensor reliability, availability, and security are growing significantly due to the growing trends towards autonomous system. An effective mean to assure the reliability and security of a sensor is to detect faulty sensors. To avoid system's failure and smooth operation due to sensor fault, system must handle and accommodate faulty sensors [4]. For example, in modern flight control system, sensor failures may cause severe problems which need to be accurately detected and isolated as soon as possible. Towards this end, various schemes have been presented in [5 - 6] and reference therein for Fault Detection and Isolation (FDI). In this connection, algorithms in Gaussian noisy environments use Kalman filter for estimation [7] or low-pass or high-pass filters [8-9]. A few of them address wireless sensor networks which use Bayesian technique [10], maximum likelihood scheme [7], or voting approaches [8] to observe and remove faulty UAV from the network. In [11], the authors have claimed that under a

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*Corresponding author: Naeem Khan; Email: nkhan@uetpeshawar.edu.pk

mild assumption the proposed decentralized scheme is capable of almost detecting faulty sensors, even if half of the neighboring sensors are faulty. Other addresses wireless sensor networks which use Bayesian technique [10], maximum likelihood scheme [12], voting approaches [13] or residual generation technique [14] to observe and remove faulty UAV from the network. A decentralized technique for fault detection has been proposed [11]. This technique was proved to detect fault(s) under some assumptions in the event bisected UAV are erroneous. Task-oriented consensus algorithm have also been developed and implemented by various scholars including the presented work in the literature [15]. The technique in [9] employs two observations, $d_{lm}(t)$ and $\Delta d_{lm}^{\Delta t}$ where $d_{lm}(t)$ is the difference between two consecutive readings "l" and "m" at instant t and $\Delta d_{lm}^{\Delta t}$ is the change of $d_{lm}(t)$ over a defined time span Δt. In the event, more than half of the tracking devices $m \in N_l$ are such that their readings are less than allowed brink reading, then the reading "l" is decided as acceptable and is subsequently used for diagnosing other sensors as good or faulty."Although this scheme has claimed to be probabilistically attractive, it is noted that the two measures are not sufficient for detecting a group of faulty sensors all together in a faulty zone. For instance, one can easily consider a situation in which a faulty sensor l has its m neighboring sensors faulty, and therefore $d_{lm}(t) = \Delta d_{lm}^{\Delta t} = 0$ for a particular time period and diagnosing the faulty sensor as good."

The current work resolve the above mentioned issue by developing a decentralized, consensus scheme for a generalized network scenario of target and followers, 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.

2. PROBLEM STATEMENT

The objective of this paper is to track a combine target in a decentralized network while maintaining a specific formation $\Re$. When all the sensors are healthy (no fault), the formation may be maintained by just keeping the relative distances constant with respect to target. However, when a sensor/UAV is unable to follow the target due to any abnormal condition, how to track the target and maintain that specific formation $\Re$ is the issue address in this paper.

3. PROBLEM SCENARIO

Among the eight (08) 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 actual target position $p(t)$. The deviation is standard deviation σ relative to the actual 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 predefined formation $\Re$ 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 $\Re$ 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 $t=0$.

4. PROPOSED ALGORITHMS

The proposed fault tolerant scheme consists of three algorithms:

1. Semi-decentralized data fusion algorithm [11, 16]

2. LOC (Line Of Communication) FDI algorithm [16]
3. CN (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.

4.1 Semi-decentralized Data Fusion Algorithm

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

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

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]

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

In the above equation, β and γ 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 1 i.e. $r = 1$.

4.2 LOC Fault Detection and Isolation Algorithm

The above discussed Semi-decentralized 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 discrepancies with the global median beyond the fixed 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 gathering 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. $|p_l - p_m| \le 2\sigma$ 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 computed. In short, any UAV requires at least three similar information in order to find correct 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 $|G.Med - p_l|$ exceeds 2σ 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.

4.3 CN (Communication with Neighbor) Fault Detection Algorithm

Beside semi-decentralized 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 enhance the accuracy of target tracking network.

(i) Semi-decentralized data fusion algorithm

Determine number of neighbors r for l^{th} UAV, M_l^r and $c_{lm}(t-(r-1)\Delta t)$ for $m \in M_l^r$

- $a_l(t+\Delta t) = (1-\beta)a_l(t) + \sum_{m\in} c_{lm}(t-(r-1)\Delta t)p_m(t-(r-1)\Delta t)$
- $b_l(t+\Delta t) = a_l(t+\Delta t) + a_l(0) + b_l(0)$

(ii) LOC fault detection algorithm.

$\left| \in M_l \right|_s$ = set of sensors (UAVs) that have similar information and can be reached from l^{th} UAV.

if

$\left| \in M_l \right|_s \geq F+1$

$G.Med_l = median(\prod{}_l)$

While

$\left| \in M_l \right|_s < F+1$

if

$G.Med_m = found$

$G.Med_l = G.Med_m$

else $\in M_l = \in M_l \cup \sum_{m \subset M_l^r} \in M_m$

$G.Med_l = median(\prod{}_l)$

if

$\left| G.Med_l - p_l(t) \right| > 2\sigma$

l^{th} UAV sensor has LOC fault

else l^{th} UAV sensor is non-faulty

(iii) LOC fault detection algorithm.

$\left| \in M_l \right|_s$ = set of sensors (UAVs) that have similar information and can be reached from l^{th} UAV.

if

$\left| \in M_l \right|_s \geq F+1$

$G.Med_l = median(\prod{}_l)$

While

$\left| \in M_l \right|_s < F+1$

if

$G.Med_m = found$

$G.Med_l = G.Med_m$

else $\in M_l = \in M_l \cup \sum_{m \subset M_l^r} \in M_m$

$G.Med_l = median(\prod{}_l)$

if

$\left| G.Med_l - p_l(t) \right| > 2\sigma$

l^{th} UAV sensor has LOC fault

else l^{th} UAV sensor is non-faulty

5. SIMULATION RESULTS

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

Fig. 1 represents the general scenario that has been considered to testify the proposed algorithms. In the Figure, the red box at the center represents the target which is tracked by eight UAVs represented by blue boxes. The black lines

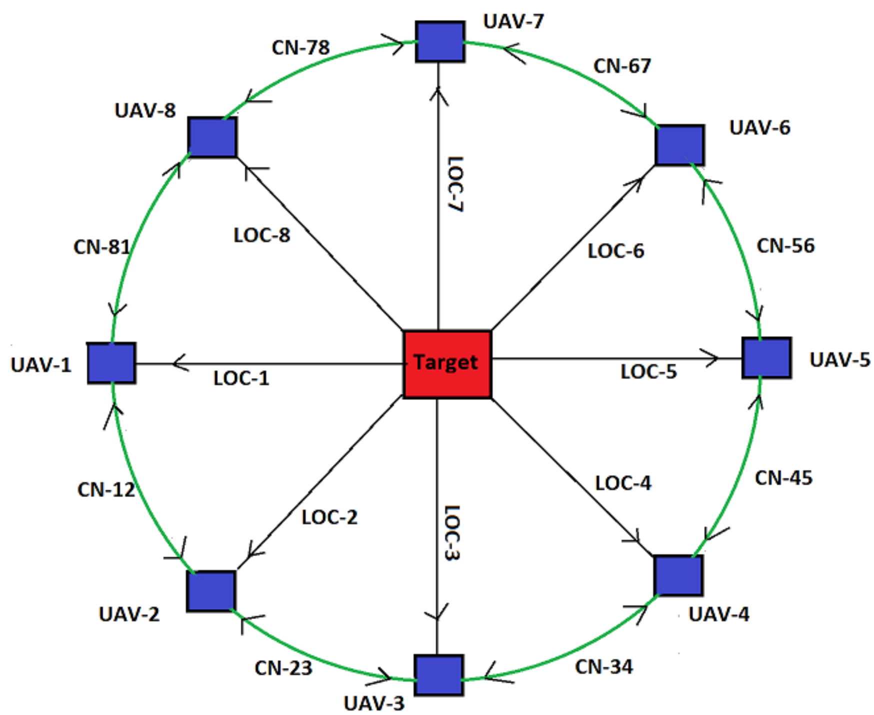

Fig. 1. Formation of UAVs to track the target.

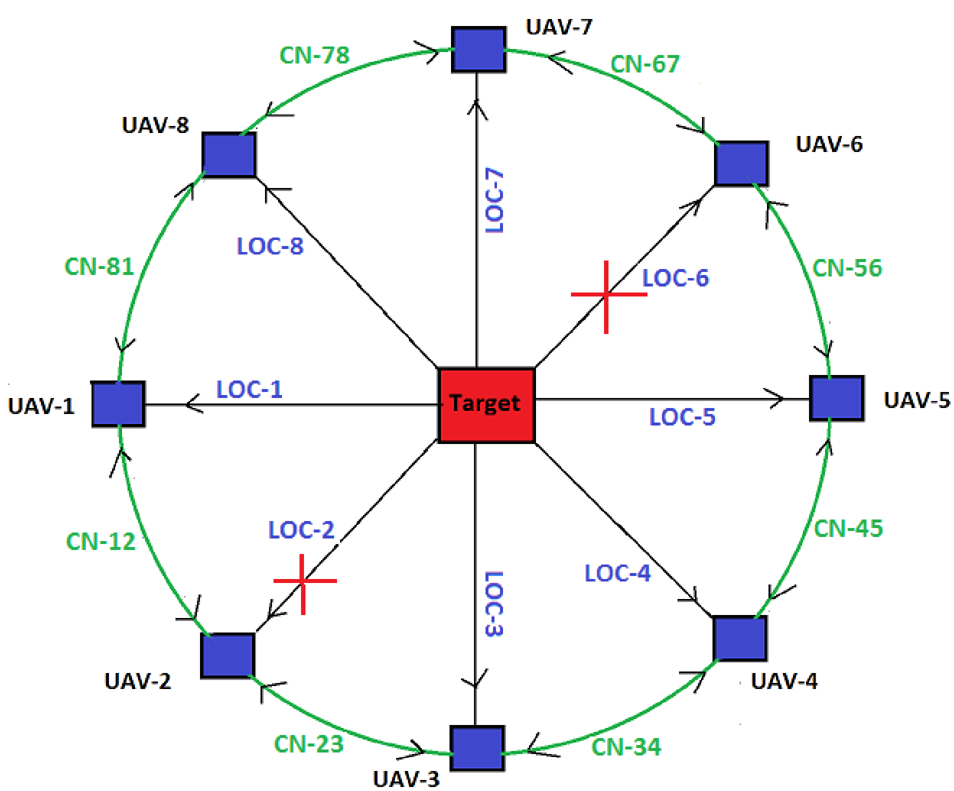

Fig. 2. Line of communication faults in UAV 2 and UAV 6.

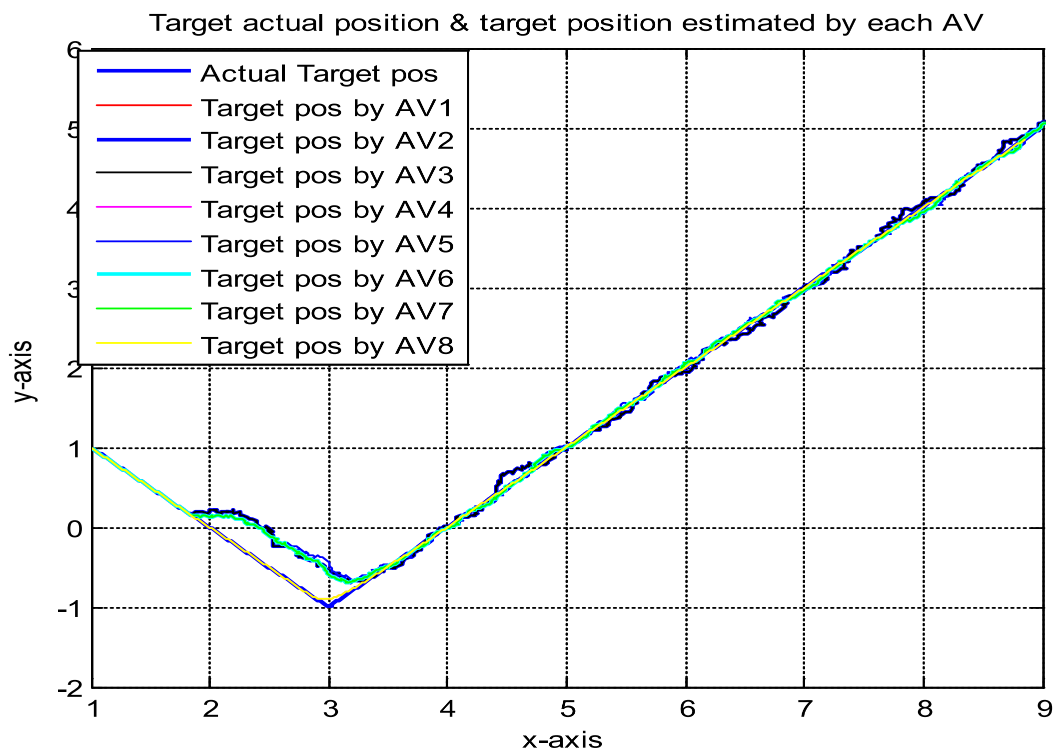

Fig. 3. Actual target position and estimation of target position by all UAVs.

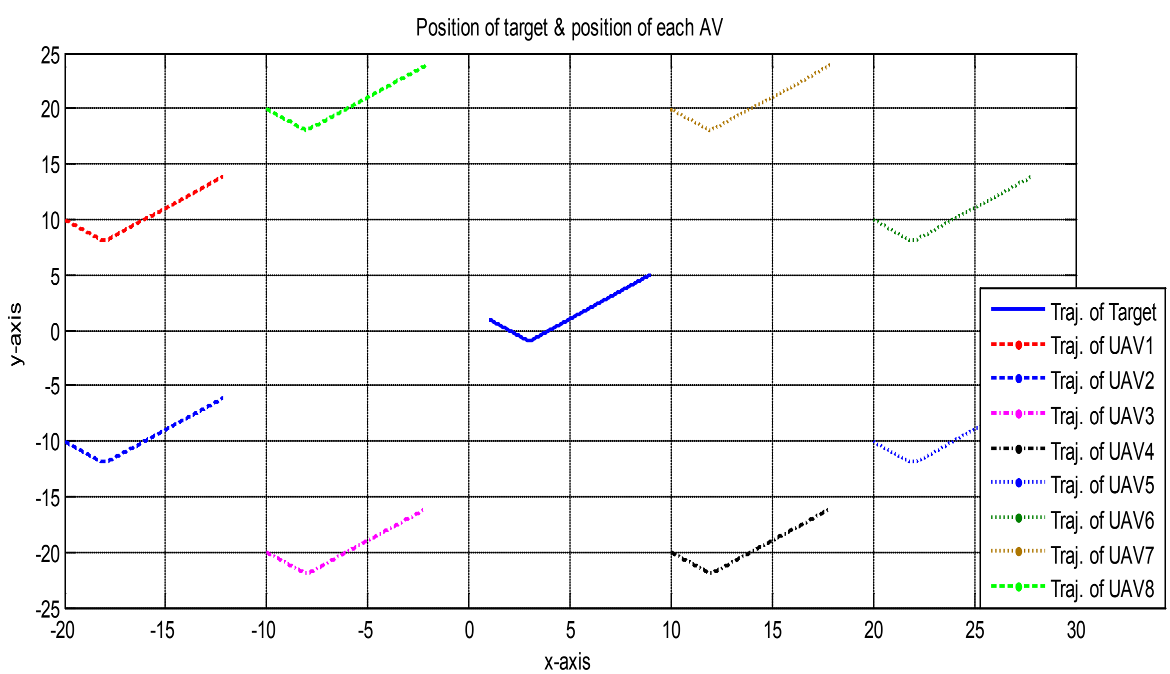

Fig. 4. Trajectories of target and UAVs (top view).

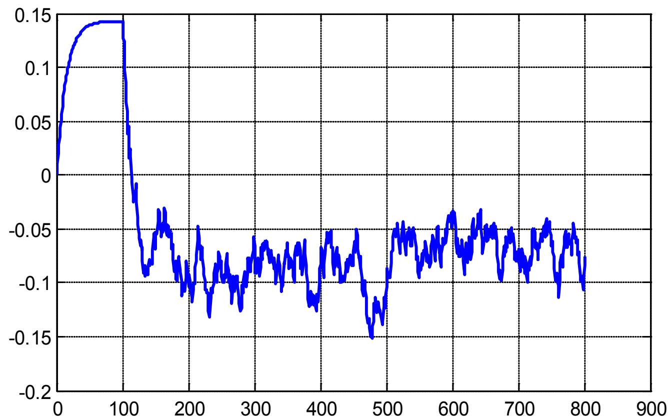

Fig. 5. Maximum possible deviation of UVA2 along Y-axis in the presence of LOC fault.

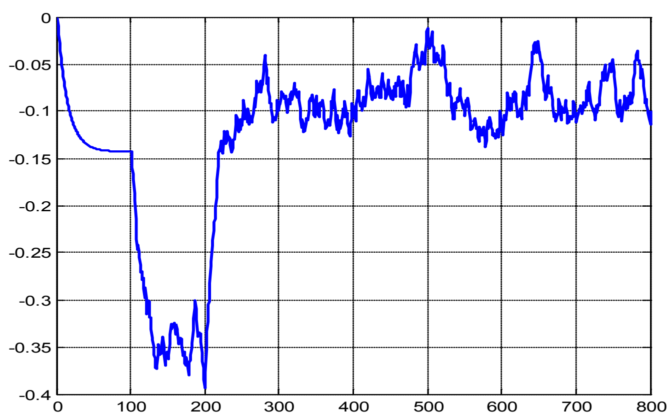

Fig. 6. Maximum possible deviation of UVA6 along Y-axis in the presence of LOC fault.

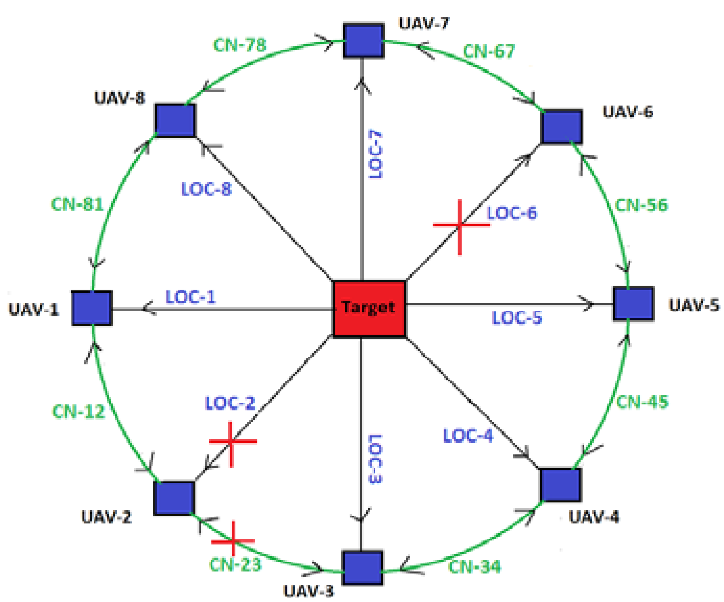

Fig. 7. Scenario for simultaneous LOC and CN faults.

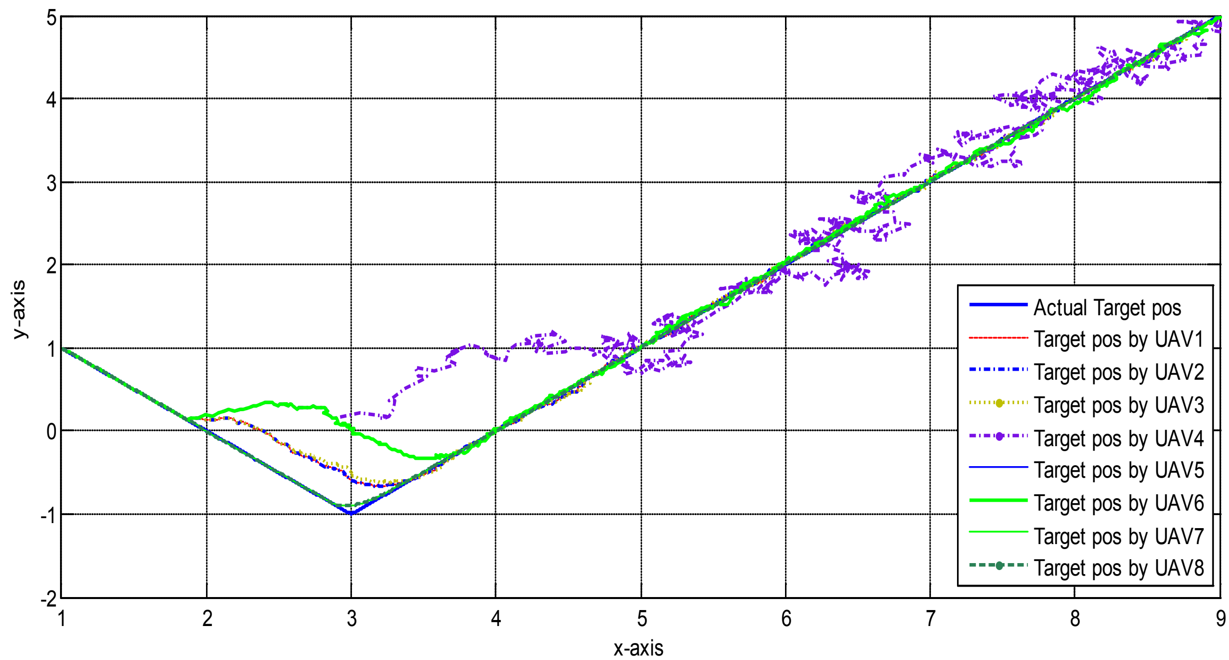

Fig. 8. Target actual trajectory and trajectories of UAVs for the scenario of Fig. 7.

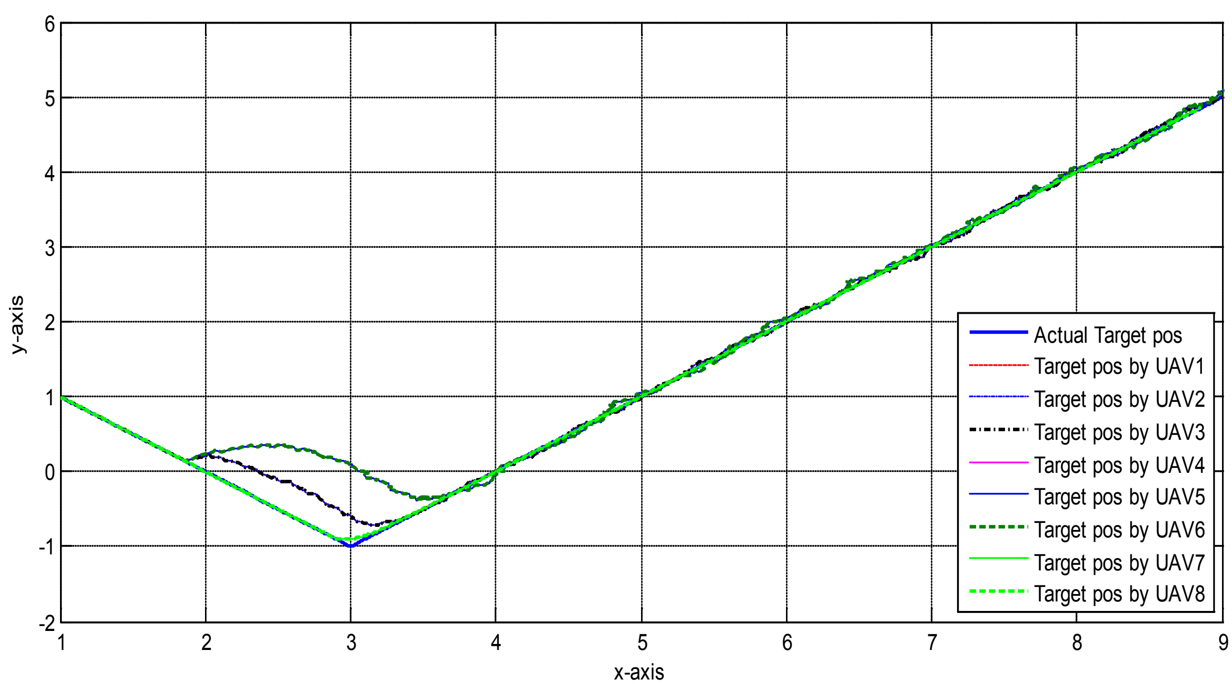

Fig. 9. Target actual position and target position estimated by each UAV using LOC and CN FDI algorithms simultaneously.

represent LOC links (connecting each UAV with target) through which each UAV senses the target position and track it down. The green 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 UAV 2 and UAV 6 cannot sense the actual target position as shown in Fig. 2. In this scenario, UAV 2 and UAV 6 are 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 (double LOC fault). Due to the employment of LOC algorithm, as shown in Fig. 3 that UAV 2 and UAV 6 are 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 both 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 2 (represented by blue line) and UAV 6 (represented by green 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. 4 shows a clear picture of trajectories of the target and the follower UAVs claiming that UAV 2 and UAV 4 (represented by red lines) are tracking the target accurately though their sensors cannot sense the target position.

Fig. 5 and 6 show the distances of UAV 6 from the target along X and Y axes increase at the instant of fault occurrence. However, upon diagnosing the fault and employing LOC-FDI algorithm, both the UAVs maintain the initial distance relative to target. Hence, the deviation does not exceed the allowed threshold limit of ±0.15. The deviation results are similar for both UAVs.

Consider another scenario where both LOC and CN faults occur simultaneously as shown below in Fig. 7. The LOC fault exists in UAV 2 and UAV 6 whereas UAV 2 and UAV 3 have CN fault which prevents information flow between them. Since UAV 2 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. 8 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.

Implementing the proposed LOC and CN-FDI algorithms simultaneously have resulted in superior performance. The affected UAV 2 is tracking the target with better result as shown in Fig. 9.

6. SUMMARY

In this paper, the proposed scheme designed for multi sensor target tracking network comprises of three algorithms: semi-decentralized data fusion algorithm, LOC fault detection and isolation algorithm and CN fault detection and isolation algorithm. The main theme is finding of global median from healthy (non-faulty) sensor readings using semi-decentralized algorithm. This global median is utilized to trace faulty and non-faulty sensors using Line-of-communication FDI algorithm and Communication-with-neighbor FDI algorithm.

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