Multiple 3D Target Tracking in Binary Wireless Sensor Network

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***Abstract*—In this paper, 3D target tracking in wireless sensor network (WSN) is considered. Unlike other published work, this paper addresses the problem of estimating locations of different targets in 3D environment. Each sensor makes T observations to get local decisions. These decisions are modulated using on-off keying (OOK) and sent to a central node called fusion center. The fusion center detects all decisions sent from all sensors to process them in order to estimate the targets locations using maximum likelihood estimator. This approach generalizes the existing work in the literature about a single target localization if we considered that the number of targets equal one. The corresponding Cramer-Rao lower bound (CRLB) has been also derived. Furthermore, simulation results are provided and discussed.**

***Index Terms*—unmanned aerial vehicles, localization, WSN, multi-target tracking, distributed detection, fusion center, CRLB**

I. Introduction

The most important issue for unmanned aerial vehicles (UAVs) is to know their current position and orientation (localization). They are of interest since they have played essential roles in industrial and military applications. Several applications on the localization are addressed [1]-[4]. In addition, recent advances in electronics have dramatically improved the degree of integration of onboard control systems for UAVs. For the outdoor applications, global positioning system (GPS) provides low errors in location estimations, and estimate the state error of the UAV trajectory if it is combined with IMU [5], [6]. However, one successful solution for the localization is based on the use of WSN. In the past few decades, WSNs have been studied extensively in the literature. WSNs have wide applications in military surveillance, security, monitoring environment, and cognitive radio networks due to their high flexibility, enhanced surveillance coverage, mobility, and cost effectiveness. WSN consists of a large number of low-cost and low-power sensors, which are deployed in an environment to collect observations and preprocess them to obtain local decisions [7]-[11]. Fig. 1 shows an example of a WSN where sensors are deployed to monitor some region and detect an intruder if once it is passing through this region. Target localization is one of the most important aspects in WSN which enables to track the target [12]. Since it is not possible to estimate target height with a single sensor due to observability problem, there is a need to combine the information considering two or more sources of wireless sensor separated geographically. Moreover, the detection reliability is increased when distributed sensors are used. Many algorithms have been proposed in the literature to localize the target, i.e., time domain of arrival (TDOA), direction of arrival (DOA), and energy based methods [13]-[19]. In [20], maximum likelihood estimator is used to estimate the location of the target where each sensor sends a row of quantized decisions to the fusion center. Depending on all rows sent by different sensors, the fusion center use maximum likelihood estimator to estimate the location of the target. Moreover, the efficiency of maximum likelihood estimator is compared with the weighted average algorithm and the CRLB. Furth work, channel aware target localization is considered in [21] where the estimation process carried out using the quantized sensor data in addition to the fading channel statistics.

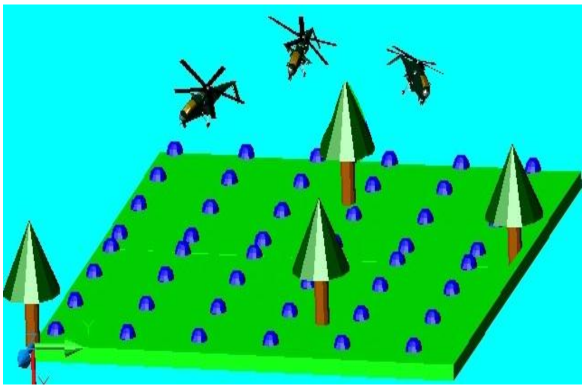

Figure 1. UAVs cross area under WSNs surveillance.

In this paper, we consider a 3D multi target localization problem where targets are flying within the range of the sensor network. On the other hand, sensors are assumed to be ground sensors where they are deployed on the ground surface plane. Moreover, sensors modulate their decisions using OOK which has been proposed recently for WSN because it is a power efficient

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modulation technique and enables sensors to use censoring scheme (send/no send).

The rest of the paper is organized as follows. In section II, system model and problem formulation are discussed. The processing of data at sensors and the fusion center is discussed in sections III and IV, respectively. Section V shows the simulation and numeric results of the proposed decision scheme. Conclusion and future work are provided in section VI.

II. System Model and Problem Formulation

A number of K sensors are deployed on the ground plane to collect observations and get local decisions. Sensors keep taking observations for T time intervals and process them to get a local binary decision about the existence of targets. We have to keep in mind that some of these decisions may include information about one target while other decisions may include information about more than one target. Then, this decision is transmitted to the fusion center. The fusion center receives all decisions sent from all sensors, and estimates the targets location based on maximum likelihood estimation theory.

The observation for the *k*-th local sensor during the *i*-th interval, $S_{k,i}$ depends on the received power emitted by (or reflected from) the target corrupted by additive white Gaussian noise. $S_{k,i}$ can be formulated as:

$$S_{k,i} = \left(\sum_{i=1}^{N} a_{k,i} \right) + n_{k,i} \tag{1}$$

where $a_{k,i}$ is a constant depends on the amount of received power at *k-th* sensor due to i-th target, and $n_{k,t}$ is the noise at *k-th* sensor during the *t-th* time frame, and *N* is the total number of targets with in the area and needed to be localized. $n_{k,t}$ is assumed to be *i.i.d* with respect to time and sensor and follows standard Gaussian distribution N (0, σ_k^2).

According to the isotropic signal intensity attenuation model, $a_{k,i}$ can be written as:

$$a_{k,i} = \sqrt{P_0 \left(\frac{d_0}{d_{k,i}} \right)^n} \tag{2}$$

where P_0 is the signal power measured at a reference distance d_0 (In this paper, we set $d_0 = 1m$), d_k is the distance between the *k-th* sensor and the target, and *n* is the path loss exponent which depends on the environment.

$$d_{k,i} = \sqrt{(x_k - x_i)^2 + (y_k - y_i)^2 + (z_k - z_i)^2} \tag{3}$$

where (x_i, y_i, z_i) is the Cartesian coordinate of the *i-th* target and (x_k, y_k, z_k) is the Cartesian coordinates of the *k*-th sensor where the sensors are deployed on the ground surface $(z_k = 0)$.

Sending a decision in each time interval (number of T decisions as a total) consumes a lot of power from the sensors. Since the WSN is subject to power constraint, we will assume that the sensor process the T observations to get one reliable decision to be sent at the end of the time observation window. Considering this algorithm a considerable amount of power is saved. The target is assumed to be stationary during the T time intervals.

III. Processing at Sensors

After taking T observations, the binary sensor sends either 1 or 0 (no send) based on the average of the T observations. Assuming *i.i.d* observations with respect to time, the local decision rule of the *k*-th sensor can be formulated as:

$$S_k = \frac{1}{T} \sum_{t=1}^{T} \left[\left(\sum_{i=1}^{N} a_{k,i} \right) + n_{k,i} \right] \underset{u_k = 1}{\overset{u_k = 0}{\lesseqgtr}} (\tau_k) \tag{4}$$

$$P(u_k = 1 \mid S_k) = Q\left(\frac{\tau_k - \left(\sum_{i=1}^{N} a_{k,i} \right)}{\sigma_k} \right) \tag{5}$$

$$P(u_k = 0 \mid S_k) = 1 - Q\left(\frac{\tau_k - \left(\sum_{i=1}^{N} a_{k,i} \right)}{\sigma_k} \right) \tag{6}$$

where τ_k is a quantization threshold, u_k is the local decision of the *k-th* sensor, σ_k is the variance of S_k, and *Q(.)* is the Q-function which is the complementary cumulative distribution function (CDF) of the Gaussian distribution.

IV. Processing at the Fusion Center

The channel between sensors and the fusion center is assumed to be error free channel. Once the fusion center receives all sent decisions, the estimation process of the parameter: $\boldsymbol{\theta}=[x_1, y_1, x_2, y_2, \ldots, x_N, y_N]^T$ is carried out. Other parameters, i.e., τ_k, σ_k, *N*, are assumed to be known at fusion center. However, efficient algorithms and estimators can be used to estimate the number targets. The likelihood estimator can be written as:

$$p(U \mid \theta) = \prod_{k=1}^{K} \left([P(u_k = 1 \mid S_k)]^{u_k} [P(u_k = 0 \mid S_k)]^{1-u_k} \right) \tag{7}$$

Taking the natural logarithm for both sides, the log likelihood estimator is obtained as:

$$\ln(p(U \mid \theta)) = \sum_{k=1}^{K} u_k \ln(P(u_k = 1 \mid S_k)) + (1 - u_k) \ln(P(u_k = 0 \mid S_k)) \tag{8}$$

$$\ln(p(U \mid \theta)) = \sum_{k=1}^{K} u_k \ln\left(Q\left(\frac{\tau_k - A_k(\theta)}{\sigma_k} \right) \right) + (1 - u_k) \ln\left(1 - Q\left(\frac{\tau_k - A_k(\theta)}{\sigma_k} \right) \right) \tag{9}$$

where $A_k(\theta) = \sum_{i=1}^{N} a_{k,i}$.

The maximum likelihood estimator can be expressed as:

$$\hat{\theta} = \underset{\theta}{\arg\max} \ln(p(U \mid \theta)) = \underset{\theta}{\arg\max}\, \ell(\theta) \tag{10}$$

Any efficient optimization method can be used to find θ that maximizes $\ell(\theta)$, i.e., particle swarm optimization (PSO), …etc.

A. Cramer-Rao Lower Bound (CRLB),

The variance of unbiased estimator of parameter can be bounded as the reciprocal of the Fisher information matrix [22], [23].

$$E\left[\left(\hat{\theta}(U)-\theta\right)\left(\hat{\theta}(U)-\theta\right)^H\right] \geq \frac{1}{J} \tag{11}$$

B. Fisher Information Matrix.

The fisher information matrix can be formulated as (3N*3N) matrix as it can be found in [20, 22, 23]:

$$J = -E\left\{\nabla_\theta \nabla_\theta^T \ln\left(p(U \mid \theta)\right)\right\} \tag{12}$$

$$= -E\begin{bmatrix} \frac{\partial^2\ell(\theta)}{\partial x_1^2} & \frac{\partial^2\ell(\theta)}{\partial x_1\partial y_1} & \frac{\partial^2\ell(\theta)}{\partial x_1\partial z_1} & \cdots & \frac{\partial^2\ell(\theta)}{\partial x_1\partial x_N} & \frac{\partial^2\ell(\theta)}{\partial x_1\partial y_N} & \frac{\partial^2\ell(\theta)}{\partial x_1\partial z_N} \\ \frac{\partial^2\ell(\theta)}{\partial y_1\partial x_1} & \frac{\partial^2\ell(\theta)}{\partial y_1^2} & \frac{\partial^2\ell(\theta)}{\partial y_1\partial z_1} & \cdots & \frac{\partial^2\ell(\theta)}{\partial y_1\partial x_N} & \frac{\partial^2\ell(\theta)}{\partial y_1\partial y_N} & \frac{\partial^2\ell(\theta)}{\partial y_1\partial z_N} \\ \frac{\partial^2\ell(\theta)}{\partial z_1\partial x_1} & \frac{\partial^2\ell(\theta)}{\partial z_1\partial y_1} & \frac{\partial^2\ell(\theta)}{\partial z_{11}^2} & \cdots & \frac{\partial^2\ell(\theta)}{\partial z_1\partial x_N} & \frac{\partial^2\ell(\theta)}{\partial z_1\partial y_N} & \frac{\partial^2\ell(\theta)}{\partial z_1\partial z_N} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ \frac{\partial^2\ell(\theta)}{\partial x_N\partial x_1} & \frac{\partial^2\ell(\theta)}{\partial x_N\partial y_1} & \frac{\partial^2\ell(\theta)}{\partial x_N\partial z_1} & \cdots & \frac{\partial^2\ell(\theta)}{\partial x_N^2} & \frac{\partial^2\ell(\theta)}{\partial x_N\partial y_N} & \frac{\partial^2\ell(\theta)}{\partial x_N\partial z_N} \\ \frac{\partial^2\ell(\theta)}{\partial y_N\partial x_1} & \frac{\partial^2\ell(\theta)}{\partial yz_N\partial y_1} & \frac{\partial^2\ell(\theta)}{\partial y_N\partial z_1} & \cdots & \frac{\partial^2\ell(\theta)}{\partial y_N\partial x_N} & \frac{\partial^2\ell(\theta)}{\partial y_N^2} & \frac{\partial^2\ell(\theta)}{\partial y_N\partial z_N} \\ \frac{\partial^2\ell(\theta)}{\partial z_N\partial x_1} & \frac{\partial^2\ell(\theta)}{\partial z_N\partial y_1} & \frac{\partial^2\ell(\theta)}{\partial z_N\partial z_1} & \cdots & \frac{\partial^2\ell(\theta)}{\partial z_N\partial x_N} & \frac{\partial^2\ell(\theta)}{\partial z_N\partial y_N} & \frac{\partial^2\ell(\theta)}{\partial z_N^2} \end{bmatrix}$$

The main diagonal entries of ***J*** are:

$$-E\left[\frac{\partial^2\ell(\theta)}{\partial x_i^2}\right] = \sum_{k=1}^{K}\beta_{k,i}\alpha_k\left(x_k - x_i\right)^2 q_k \tag{13}$$

where

$$\beta_{k,i} = \frac{P_o d_o^n n^2}{8\pi\sigma_k^2}\left(d_{k,i}\right)^{-(n+4)}$$

$$\alpha_k = e^{\frac{-(\tau_k - A_k(\theta))^2}{\sigma_k^2}}$$

$$q_k = \left(\frac{1}{Q\left(\frac{\tau_k - A_k(\theta)}{\sigma_k}\right)} + \frac{1}{\left[1 - Q\left(\frac{\tau_k - A_k(\theta)}{\sigma_k}\right)\right]}\right)$$

By symmetry:

$$-E\left[\frac{\partial^2\ell(\theta)}{\partial y_i^2}\right] = \sum_{k=1}^{K}\beta_{k,i}\alpha_k\left(y_k - y_i\right)^2 q_k \tag{14}$$

$$-E\left[\frac{\partial^2\ell(\theta)}{\partial z_i^2}\right] = \sum_{k=1}^{K}\beta_{k,i}\alpha_k\left(z_k - z_i\right)^2 q_k \tag{15}$$

The off diagonal entries of J are:

$$-E\left[\frac{\partial^2\ell(\theta)}{\partial x_i\partial y_j}\right] = \sum_{k=1}^{K}\sqrt{\beta_{k,i}\beta_{k,j}}\,\alpha_k\left(x_k - x_i\right)\left(y_k - y_j\right)q_k \tag{16}$$

$$-E\left[\frac{\partial^2\ell(\theta)}{\partial x_i\partial z_j}\right] = \sum_{k=1}^{K}\sqrt{\beta_{k,i}\beta_{k,j}}\,\alpha_k\left(x_k - x_i\right)\left(z_k - z_j\right)q_k \tag{17}$$

$$-E\left[\frac{\partial^2\ell(\theta)}{\partial y_i\partial z_j}\right] = \sum_{k=1}^{K}\sqrt{\beta_{k,i}\beta_{k,j}}\,\alpha_k\left(y_k - y_i\right)\left(z_k - z_j\right)q_k \tag{18}$$

$$-E\left[\frac{\partial^2\ell(\theta)}{\partial x_i\partial x_j}\right] = \sum_{k=1}^{K}\sqrt{\beta_{k,i}\beta_{k,j}}\,\alpha_k\left(x_k - x_i\right)\left(x_k - x_j\right)q_k \tag{19}$$

$$-E\left[\frac{\partial^2\ell(\theta)}{\partial y_i\partial y_j}\right] = \sum_{k=1}^{K}\sqrt{\beta_{k,i}\beta_{k,j}}\,\alpha_k\left(y_k - y_i\right)\left(y_k - y_j\right)q_k \tag{20}$$

$$-E\left[\frac{\partial^2\ell(\theta)}{\partial z_i\partial z_j}\right] = \sum_{k=1}^{K}\sqrt{\beta_{k,i}\beta_{k,j}}\,\alpha_k\left(z_k - z_i\right)\left(z_k - z_j\right)q_k \tag{21}$$

V. Simulation and Numeric Results

In this section, we introduce the simulation results of the target tracking system, which has been described earlier, using MATLAB. The proposed maximum likelihood estimator was derived for N targets but two targets have been assumed in the environment to simplify the simulation. The Cartesian coordinates of the two targets are (5, 5, 4) and (-5, -5, 3). Other parameters of the system have been set to the following values:

- P_0=25000 is assumed to be equal for both targets.
- τ_k is set to be 10 for all sensors.
- n=2 (the path loss exponent).
- $\sigma_k^2 = 1$ for all sensors.

Simulations have been carried out for different values of number of sensors which are uniformly deployed around the target. The mean square error (MSE) of the estimated target location has been calculated and compared to the CRLB for different number of sensors. The MSE of estimating *x, y,* and *z* coordinates of target 1 has been plotted vs. the square root of total number of sensors in Fig. 2, Fig. 3 and Fig. 4, respectively. On the other hand, the MSE in *x*, *y*, and *z* coordinates of target 2 has been plotted vs. the square root of total number of sensors in Fig. 5, Fig. 6 and Fig. 7, respectively. From these figures, one can observe that the performance of the likelihood estimator approaches the CRLB as the number of deployed sensors increases. In addition, Fig. 8 shows one example of two targets placed in 3D space to be localized using (10*10) binary sensor network where 100 sensors are deployed on the ground surface plane. The locations of the 2 targets are (40, 40, 4) and (-40, -40, 3) and the other parameters are set as before. Moreover, the observation interval has been set to 20. To maximize the likelihood function, PSO algorithm is used. The real locations of the 2 targets are shown as red circles while the estimated locations are shown as black circles. The obtained estimated locations of target 1 and 2 are, respectively; (36.2553, 38.4682, 3.3205) and (-37.0593, -37.9490, 1.5082). A top view of the WSN with the two targets and the estimated locations are shown in Fig. 9. The estimated distance (D_{12}) between the two targets is a matter of interest in some applications as it is shown in Fig. 10. Thus, after estimating the locations of the two targets, the estimated distance can be easily found. For the last example the real distance is 113.1415 meters while the estimated distance is 105.9146 meters.

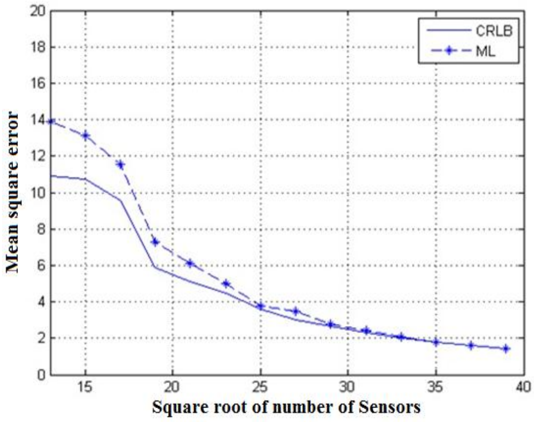

Figure 2. Mean square error of x-Cartesian of target 1.

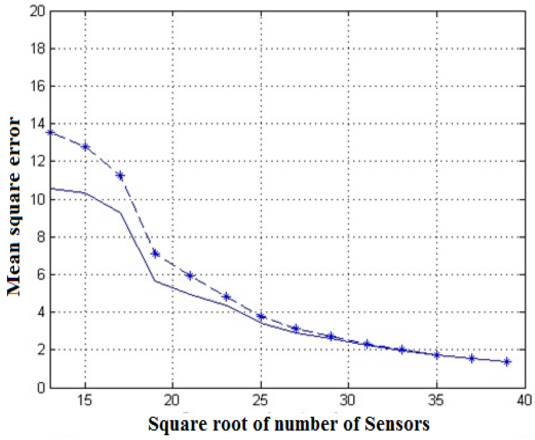

Figure 3. Mean square error of y-Cartesian of target 1.

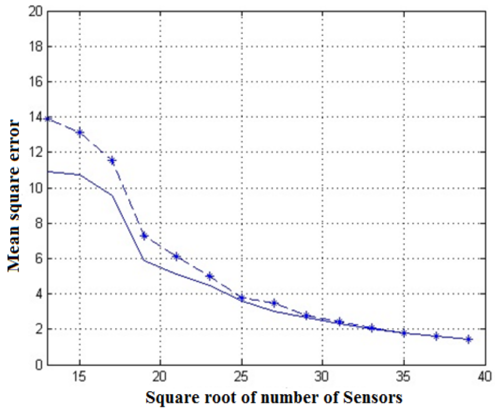

Figure 4. Mean square error of z-Cartesian of target 1.

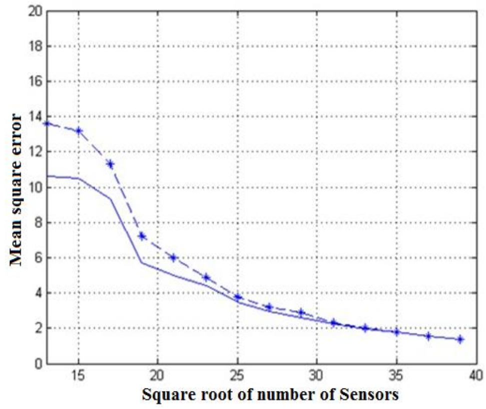

Figure 5. Mean square error of x-Cartesian of target 2.

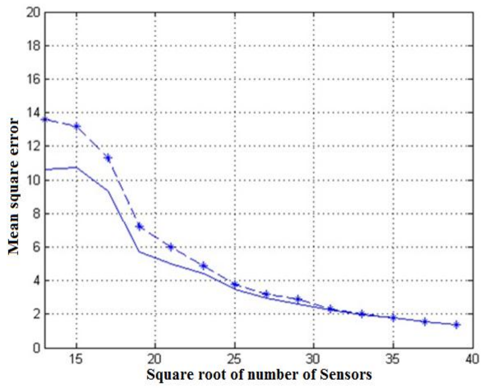

Figure 6. Mean square error of y-Cartesian of target 2.

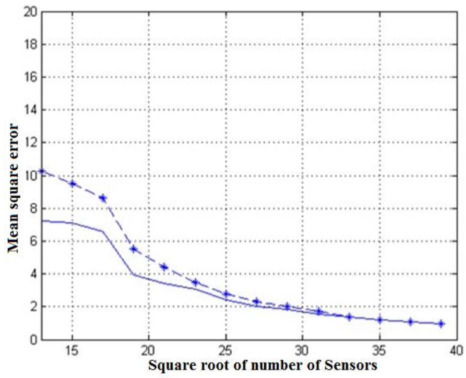

Figure 7. Mean square error of z-Cartesian of target 2.

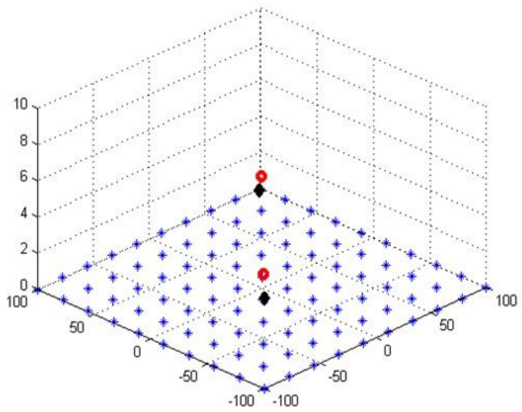

Figure 8. 3D show of the 2 targets and the WSNs.

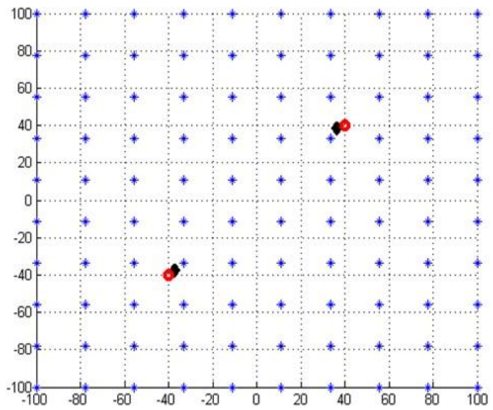

Figure 9. 2D top view show of the 2 targets and the WSN.

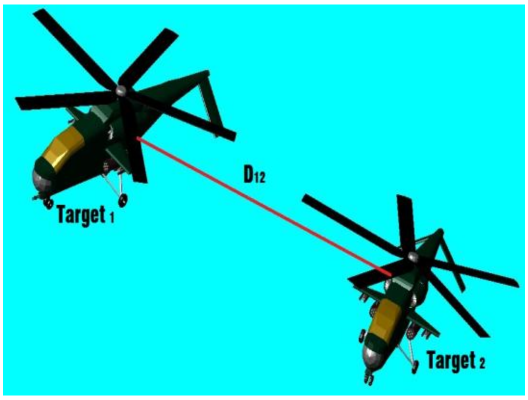

Figure 10. The estimated distances between the targets

VI. Conclusion and Future Work

In this paper, we discussed the problem of multi 3D target tracking using binary sensor network. The maximum likelihood estimator is derived and the environment of such system is simulated for 2 targets using MATLAB software. The MSE of the Cartesian of each target has been shown. However, the effect of channel between sensors and the fusion center has not been considered in this work. A future work may include the effect of the channel on the system performance.

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