Using unmanned aerial vehicles as a carrier of different sensors in NEC environment

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Abstract. The following article describes the possibilities of UAV (Unmanned Aerial Vehicles) in the area of NEC (Network enabled capability) in armed forces domain as a natural aspect of modern technologies development. UAVs equipped by radar technique might be able to affect decision making process during the military operations. The task is to devise the methodology, which will allow to dispose the sensors in the operation area in order to achieve the most accurate coordinates of detected target.

Keywords: NEC, Network enabled capability, UAV, sensors, TDOA.

1 Introduction

Nowadays, the most important attribute across the range of conducting the military operations is the timeous information gathering as a reason of increased amount of the information which is supposed to be available for each operation staff and for all command level while decision making process is in conduct. The main way of how to gather information is the reconnaissance. Since the modern technology development is in progress, more UAVs are employed by armed forces for that purpose. In case of necessity, UAVs are capable to be equipped by various sensor technology. Furthermore, once the NEC architecture and its necessary services are implemented across the armed forces, information gathered from those sensors could be easily used across different level of command.

Advantages of the task solution in the NEC area:

- high-speed network for data transferring
- minimal failure of data transfer ratio
- maximum level of data transfer security
- confidentiality
- real-time transfering of data

2 Problem formulation

We can suggest, that U, S, T are sensors which each UAV consist of and Z is the aim, which position we would like to detect. TDOA principle (Time difference on arrival) will be used as the main detection method of the object localization.
The most valuable advantage of this method is the fact that the more accurate coordinates of detected object we need, the more necessary it is to identify the accurate distance between sensors and time differences between each input signal at each individual sensor. There are no such difficulties to accomplish those conditions nowadays. The time intervals could be measured in nanosecond time-accuracy, what makes the accuracy of the detection in hyperbolic system more advanced.

3 Principal of TDOA as a method of hyperbolic location

The main condition of the TDOA is the fact that there must be three receivers at least, which are necessary for location. Receivers are dislocated in operational area and their locations are given.

We can assume that U,S,T are sensors and their locations are given by coordinates U[x_U,y_U], S[x_S,y_S], T[x_T,y_T] and Z[x_Z,y_Z] is considered as an unknown coordinates of the object to be located.

Then:

$$ZU = R_{UC} = c.t_U \quad ZS = R_{SC} = c.t_S \quad ZT = R_{TC} = c.t_T$$
$$US = L_{US} = c.t_{CU} \qquad TS = L_{TS} = c.t_{CT} \tag{1}$$

Where c expresses velocity of the light and t_U, t_S, t_T, t_{CU}, t_{CT} are time intervals of signal transition between sensors and the object or vice versa.

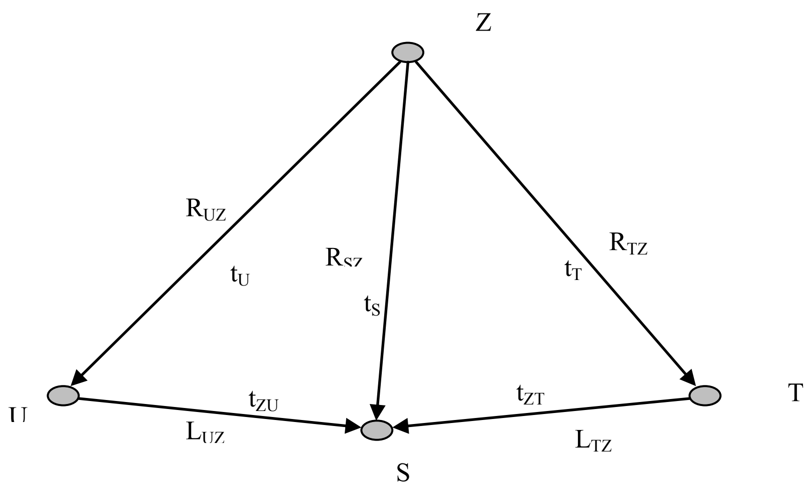

Fig. 1. Principal of TDOA as a method of hyperbolic location

Time differences could be expressed as following:

$$(t_U + t_{ZU}) - t_S = \tau_{UC}$$
$$(t_T + t_{ZT}) - t_S = \tau_{TC} \qquad \textbf{(2)}$$

Following formulas can be used for the calculation of hyperbolic coordinates:

$$\tau_U = \tau_{UC} - \frac{L_{UZ}}{c} \qquad \tau_T = \tau_{TC} - \frac{L_{TZ}}{c} \qquad \textbf{(3)}$$

where L_{UZ} and L_{TZ} are distances between sensors and τ_{UC}, τ_{TC} are the time differences of signal transmission.

For better expression, it is necessary to transform hyperbolic coordinates into right angle coordinates system, which can be easily displayed in cartesian coordinate system.

$$\tau_T = \frac{1}{c}\left(\pm\sqrt{(x - x_P)^2 + (y - y_P)^2} \pm \sqrt{x^2 + y^2}\right)$$
$$\tau_U = \frac{1}{c}\left(\pm\sqrt{(x - x_L)^2 + (y - y_L)^2} \pm \sqrt{x^2 + y^2}\right) \qquad \textbf{(4)}$$

where τ_T and τ_U are hyperbolic coordinates of the signal source and x and y are right angle coordinates of the signal source.

4 Sensor dislocation optimization in 2D area

The accuracy of the TDOA method depends on the following three factors:

- accuracy of each individual sensor,
- appropriate estimation of target dislocation,
- sensor dislocation in consideration of target.

In this case we will deal with the issue of how sensor dislocation and dislocation optimization can affect an estimate of the target position.

Target position estimate is complex variable, which is affected by several input parameters. From our perspective, the most important parameters are distance between sensor and target, distance between each pair of sensors and an angle between each individual sensor and target.

Let assume that sensors and the target are stationary and they are dislocated in 2D, sensors are dislocated in a around the circle and the target is right in the middle.

During the testing and evaluation of effectiveness of estimate, the Cramer-Rao inequality is used. The main goal is to express a lower bound on the variance of estimators.

Cramer-Rao inequality for target vector $\bar{p} \in R^D$ and sensors $\bar{q_i} \in R^D$, where D expresses 2 or 3 dimensional area and M expresses the quantity of sensors, can be defined by[1]:

$$CRB = J^{-1} = (v\sigma)^2 (GG^T)^{-1} \quad \textbf{(5)}$$

where:
$G = [g_{ij\,...}]$, (i,j)∈ I, $\quad \bar{g}_{ij} = \bar{g}_i - \bar{g}_j$, $\quad \bar{g}_i = \frac{\bar{q}_i - \bar{p}}{\|\bar{q}_i - \bar{p}\|}$
where:
J ... is the Fischer information matrix,
$\bar{g}_i$ ... is the vector heading from the target *p* to sensor *i,*
$\bar{g}_{ij}$ ... is difference between two direction vectors,
σ^2 ... expresses an error variance caused by Gauss noise. Set I consists of each individual sensor pair (i,j). Matrix G contains all vectors $\bar{g}_{ij}$, where (i,j)∈ I.

Various approaches are used to achieve the most accurate results of localization process.

The most common strategy is to minimize the trace of CRB:

$$\min f_{CRB} = tr[J^{-1}] = (v\sigma)^2 tr[(GG^T)^{-1}] \quad \textbf{(6)}$$

or we can figure out the maximum of trace of FIM:

$$\max f_{FIM} = tr[J] = \frac{1}{(v\sigma)^2} tr[GG^T] \quad \textbf{(7)}$$

Required conditions for calculation min f_{CRB} are:

1. $\sum_{i=1}^{M} \bar{g}_i = \bar{0}$
2. For matrix *D x M* $g = [g_1 \; ... \, g_M]$ must be $gg^T = \frac{M}{D} I$

where:

$\bar{g}_i$ ... is vector heading from target *p* to sensor *i*,
M ... the number of sensors,
D ... area dimension,
I ...expresses matrix, where elements on the main diagonal of the matrix are equal to 1

In case of 2D area, the solution is the matrix, where there is the same angle between each neighbor sensors. We can express it as following:

$$\alpha_i = \alpha_0 + \frac{2\pi}{M}(i-1)(i = 1,2 \dots, M) \tag{8}$$

where:
α_i ... is an angle of "i" sensor
α_0 ... is difference between first sensor and zero angle
M ... is the number of sensors.

For another matrices, where formula (8) is not applicable but matrices are capable to fulfill conditions of minimization of trace of CRB, the following formula can be applicable:

$$\sum_{i=1}^{M} \cos(\alpha_i) = 0 \quad \sum_{i=1}^{M} \sin(\alpha_i) = 0$$

(9)

$$\sum_{i=1}^{M} \cos(2\alpha_i) = 0 \quad \sum_{i=1}^{M} \sin(2\alpha_i) = 0$$

Table 1 shows an example of dislocation of seven sensors where formula (8) is not applicable, but formula (9) is.

Table 1. An example of sensor dislocation

Sensor	Angle α_i	$x_i = cos(\alpha_i)$	$x_i = sin(\alpha_i)$	$x_i = cos(2\alpha_i)$	$x_i = sin(2\alpha_i)$
1	0°	1	0	1	0
2	53°	0,601	0,798	-0,277	0,961
3	100°	-0,174	0,985	-0,941	-0,342
4	158°	-0,927	0,375	0,718	-0,695
5	202°	-0,927	-0,375	0,718	0,695
6	260°	-0,174	-0,985	-0,941	0,342
7	307°	0,601	-0,798	-0,277	-0,961
$\sum$		0	0	0	0

Both solutions are applicable only in case we considered earlier, so that sensors are dislocated around the circle and target is right in the middle.
Table 1 shows that matrix of sensors meets conditions in formula (9) and represents the group of sensors, whose dislocation is optimized for the most accurate estimate of target's position.

5 Conclusion

An estimate of target position is difficult process, which is influenced by several input values, e.g. distance between sensor and the target, randommodification of target position and the distance of each individual sensor in case of sensor network installed.

In this paper we were dealing with the optimization strategy of sensors and the target dislocation. Both sensors and target were dislocated in 2D area around the circle and target was situated right in the middle.

Further on, it would be useful to focus on cases, e.g. sensors are set only in a certain, predetermined cone of observation area (to avoid being compromised or in cases where observation area is inflicted by obstacles).

Both methods require mathematical description/formulation of 3D area since it is the most accurate and reflects real conditions.

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