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A New Method for Geolocating Radiation Sources Based on Evolutionary Computation of TDOA Equations

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ABSTRACT

In this article, a new method is introduced for geolocating signal emitters which is based on evolutionary computation (EC) concept. In the proposed method, two well-known members of EC techniques including Bees Algorithm (BA) and Genetic Algorithm (GA), are utilized to estimate the positions of emitters by optimizing the hyperbola equations which have been resulted from Time Difference of Arrival (TDOA) of their radiated signals. To show the effectiveness of the EC concept in positioning, the simulation is carried for linear and nonlinear moving emitters in the presence of several amounts of noise. Then, the obtained results are compared with Maximum Likelihood (ML) estimator as one of the most common approaches among traditional methods. The results show better performance of the EC family compared to ML in such way that they estimate the position of emitters even up to 33% and 30% more accurate than ML in the presence of 5 and 10 percent of noise, respectively. Furthermore, the comparison among the examined methods belong to EC family shows that BA leads to the accuracy of 3 to 12 percent better than GA in estimating positions of radiation sources.

1. Introduction

The Geo-Location is one of important issues in modern technology which has several applications in military and wireless communications [1-4]. In this method, the position of an emitter is estimated by using its received signal. Several techniques have been proposed to perform more accurate positioning which each of them has had some advantages and shortcomings. One of the primary Geolocation methods utilizes the Angle of Arrival (i.e. AOA) of the received signal to determine the position of its emitter. As the signals may travel with straight direction, therefore in crowded structures the AOA method is not an appropriate solution [1,5], furthermore the cost of maintaining and calibrating of antennas in this method is very high [6]. Time of Arrival (TOA) of a signal is the time of its travelling from source to a receiver. A number of Geolocating methods combine TOA and some geometric approaches like triangulation to estimate the location of the source [7, 8]. Unfortunately, the performance of the TOA method depends on signal path and time synchronization between source and receivers. Some other methods make use of Time Difference of Arrival (TDOA) to solve the problems arise from TOA approach [1,9,10]. TDOA is a passive method which uses the absolute time of arrival at a certain base station rather than the measured time difference between departing from one and arriving at the other station. So, there is no need to have synchronization between source and receivers. The performance of this method is excellent compared to the mentioned alternatives when there is not any straight path between source and receivers [1, 9]. In addition, TDOA method is more secured and nobody aware of the presence of the receiver in the environment, due to its passiveness [11]. In this method, each of sensors receives the transmitted signal by a certain delay compared to the received version by a reference receiver. The mentioned delay makes a hyperbolic locus in Cartesian coordinate system [12]. Then, the location of the source is determined as the intersection of the hyperbolas constructed from delays between different sensors and the reference receiver. It is proofed that at least four receivers (a reference and three other receivers) are needed to perform source estimation in TDOA approach [13]. The mentioned hyperbolic equations are highly nonlinear and there is no unique and systematic method to solve multidimensional parabolic equations. Furthermore delays on the right side of above equations are not always exact and usually contain considerable amount of noises, therefore hyperbolas have not exact intersection. Accordingly, direct based solutions are not appropriate to solve this kind of equations and consequently, the localization problem becomes as a searching problem.

Several methods including numerical and optimization techniques have been proposed to solve this challenging problem. For example, the method that was suggested by Fang [14] which unfortunately is not so beneficial in the presence of more than four sensors. A more general situation with extra measurements was considered by Friedlander [15], Schau and Robinson [8], and Smith and Abel [16, 17]. Although in these methods the closed-form solutions have been developed, but the estimators were not optimum and the results were not appropriate. Taylor method was proposed in [18] and [19] to solve hyperbola equation. This process starts by primary and basic premise and then continues by using linear Least Square (LS). The shortcoming of these methods is mainly their dependence on the basic premise. Sometimes, bad premises caused to trapping into local minima. To solve this problem Chan offered a two steps method based on LS and maximum Likelihood (ML) approaches [19]. The performance of this method is acceptable only in low noise conditions.

Evolutionary Computation (EC) are population-based stochastic optimization technique which imitates swarm's pattern of behavior in conducting their function. Recently, several methods which have been based on the EC concept have become very popular mainly to address optimization problems such as train scheduling, timetabling, shape optimization, telecommunication network design and several problems in computational biology [20]. In this paper, evolutionary computation framework is employed to provide more accurate and robust solution for TDOA equations. Two well-known members of EC techniques - Genetic Algorithm (GA) and Bees Algorithm (BA)-are utilized to optimize the TDOA equations which lead to estimate the coordinates belonging to the intersection of the TDOA hyperbolas.

The rest of the paper is organized as follows. In Section 2, the proposed algorithm is introduced includes modeling of TDOA equations in EC framework followed by optimizing them by BA and GA. In section 3, the performance of the proposed method is evaluated on simulated targets. In section 4, the obtained results from simulations are compared to the results of a traditional method by using some effective parameters. Conclusion is presented in the last section of the paper.

2. THE PROPOSED METHOD

In TDOA based localization, there are some sites each of them may receive the radiated signal from an unknown emitter. The radiated signal arrives to each of receivers by a delay which differs from delays belong to other sites due to their different distances from emitter. In general there are at least four receivers which one of them is considered as reference.Then, measurements of distances and times are performed respect to the reference sensor. Figure (1) shows such geometry in which the positions of radiation source (p_s) and receiver sites p_i are illustrated as:

$$p_s \equiv [x_s, y_s, z_s]^T \tag{1}$$
$$p_i \equiv [x_i, y_i, z_i]^T \qquad i = 0,1,2,3$$

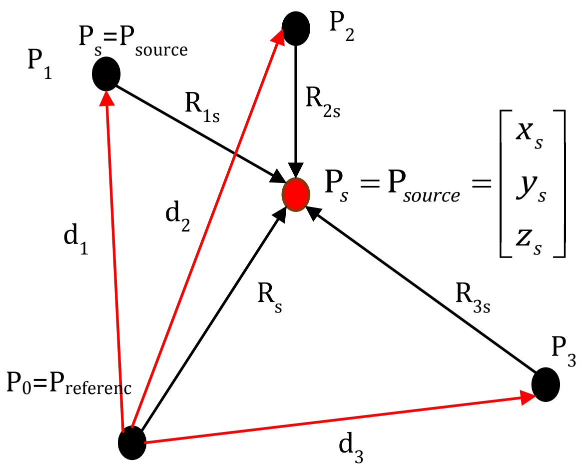


Figure 1: The topology of TDOA- based Geo-location in the presence of four fixed receiver's arrangement in 3D space.

P_0, P_1, P_2 and P_3 are described respectivelyas:

$$P_0=\begin{bmatrix}x_0\\y_0\\z_0\end{bmatrix},P_1=\begin{bmatrix}x_1\\y_1\\z_1\end{bmatrix},P_2=\begin{bmatrix}x_2\\y_2\\z_2\end{bmatrix},P_3=\begin{bmatrix}x_3\\y_3\\z_3\end{bmatrix}.$$

Suppose that Δt_i shows the difference between times that the signal is received in i^{th} sensor (t_i) and the time that the signal is received in the reference sensor (t_0). The relation between TDOA and the passed distance by signal between these two receivers may be simply written as:

$$d_i=c(t_i-t_0) \qquad i=1,2,3 \tag{2}$$

in which c represents the speed of travelling of the signal. Based on definition of d_i the difference of distances which have been passed by signal between each receiver site and the reference sensor may be written in terms of Euclidian distances. Noting this fact that there are three sensors which are compared to the reference, three parabolic equations are formed as:

$$\sqrt{(x_s-x_i)^2+(y_s-y_i)^2+(z_s-z_i)^2}-\sqrt{(x_s-x_0)^2+(y_s-y_0)^2+(z_s-z_0)^2}=d_i \tag{3}$$
$$i=1,2,3$$

In the next section, the evolutionary computation paradigm is used to solve the above equations.

2.1. Geolocation by Using BA

The colony of bees is a composition of three groups of bees including: employed bees, onlooker bees and scout bees. Figure (2) is dedicated from figure (1) to show arrangement of four receivers and the mechanism of BA to find source position. This mechanism is mainly based on using scout bee's information and onlooker bee's imitation to pursuing scouts datum of candidate sites.

The aim of this algorithm is to find flower paths with more amount of nectar by less effort [21, 22]. Firstly, the scout bees construct a random neighborhood to find a food source that has adequate amount of nectars (i.e. a potentiated solution for source position). This food source should satisfy fitness function which is concluded from equation (3). Then scout bees return to a place near hive that is named "dance floor" to perform a kind of motion which is known as "waggle dance" [23, 24]. This dance consists of information about position and cost of elite candidate sites. Onlooker bees who are waiting in the hive, try to imitate the waggle dance to find the direction of elite site may be more prominent for next searches. Therefore, the food source vectors are initialized by scout bees as:

$$V_m=LB+rand\times(UB-LB) \tag{4}$$

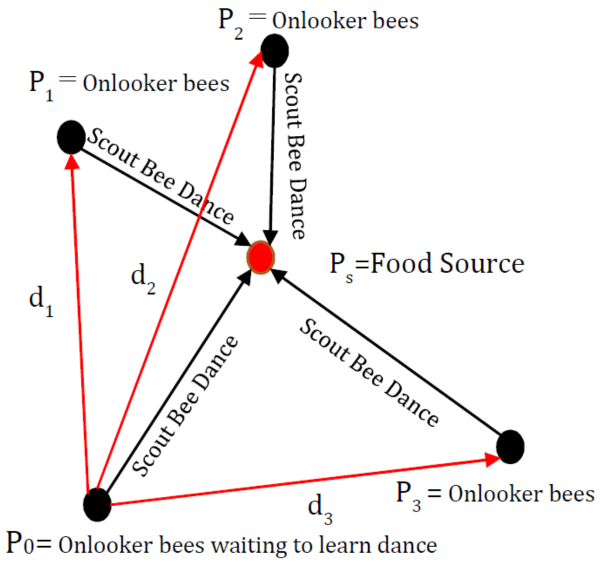


Figure 2: topology of Bees algorithm to find source location by using scouts information.

In which V_m, LB and UB demonstrate m^{th} solution, lower and upper bounds of solution range, respectively. Further $rand$ shows the generating function of random values in region $[0\ \ 1]$. For brevity set of equations (3) is re-written as:

$$\|p_s-p_i\|-\|p_s-p_0\|=d_i \qquad i=1,2,3 \tag{5}$$

in which p_s and p_0 are considered as coordinates of source and reference receiver as mentioned before. Furthermore p_i is coordinates the locations of other receivers. As V_m is a candidate for source position, therefore mounting it in equation (5), leads to errors $[e_1,e_2,e_3]$ as:

$$\|V_m-p_1\|-\|V_m-p_0\|-d_1=e_1 \tag{6}$$
$$\|V_m-p_2\|-\|V_m-p_0\|-d_2=e_2$$
$$\|V_m-p_3\|-\|V_m-p_0\|-d_3=e_3$$

Scout bees measure amount of nectar and sugar of each explored place when they returned to the hive. In our problem that means they evaluate the profitability (i.e. accuracy of source candidate) after they find a neighbor food source. Thereafter, the fitnessfunction is evaluated using the following equation in order to minimize the error:

$$F(V_m) = abs(\|e_1\| + \|e_2\| + \|e_3\|) \tag{7}$$

in which $F(V_m)$ is the objective function value which is computed for the solution vector V_m. Then, employed bees search again for new food sources with more nectar within the neighborhoods of the food source V_m (new potentiated source position). After a food source V_m for an onlooker bee is probabilistically chosen, a positive feedback behavior appears. This allows the colony to gather food quickly and efficiently.By analyzing this piece of information by onlooker bees that are waiting in the hive, they choose the food sources based on the probability of profitable sources. This probability is estimated by fitness values which are provided by employed bees as:

$$PV = \frac{F(V_m)}{\sum_{m=0}^{M} F(V_m)} \tag{8}$$

Paths with sufficient amount of nectar will be visited with more bees and on the other hand, paths with less nectar are visited with fewer bees and they will be shrunk. This means there is a contraction in paths sizes after iteration. The entire process is repeated up to converging to fittest location as described in pseudo codeof figure (3).

1- ***Set*** *upper and lower bounds.* $(LB$ and $UB)$
2- ***Initialize*** *n random population of bees, food sources, scouts*
3- ***While*** *(Counter < Iteration),* ***Do***
4- ***For*** *bee=1 to Number of Bees ,* ***Do***
 ****Select*** *m random Preliminary selection sites as fittest source positions.*
 ****Send*** *scout bees to random known food sources (Source prone locations are as* $v_0 \equiv [X_{random}, Y_{random}, Z_{random}]$ *)*
5- ***Calculate*** *fitness function for each bee*
 Calculate *new delays for random population*
 Compare *new delays with current delays*
 Update *locations and select the fittest position*
 Recruit *bees for selected sites*
 (Best elite sites are as best estimation positions)
 Send *onlooker bees to these selected elite's locations.*
 Else *shrink paths with low probability.*
 End
6- ***Do*** *neighborhood search*
7- ***Send*** *scout bees for better results*
8- ***If (****probability is higher than current),*
 Send *onlookersand upgrade the results*
 Else *current location is solution*
 End
Return *results and locations*

Figure 3: The pseudo code of the applied BA for Geo-location.

2.2. Geolocation by Using GA

The goal of genetic algorithm is to optimize equation (3) in such way that the exact position of emitter is found. Figure (4) describes the procedure of Geolocating by using GA.

Start
While *not termination* ***do***
 Set *upper and lower bound* $(LB$ and $UB)$
 Create *a group of chromosomes*
Select *two parents in the population*
Insert *two random offspring into generation*
 Compute *fitness of each chromosome by usingEq.7*
 Calculate *probability of each selected chromosomes*
 Select *fittest chromosomes by using Rolette wheel*
If*fittest chromosomes improvesEq.6*
Select*chromosomes as new source location*
 Else
 Create *new population mating pool by calculating CDF*
 Mutate*offspring with scaling (natural coding)*
Update *the estimated source location*
End while

Figure 4: mechanism of GA optimization to find the correct position of emitter.

In the first step, several primary population is generated which is named chromosomes (similar to equation (4) in the section describing BA) where each of chromosomes contains some genes as candidates for coordinates of the source. In the next step, a fitness function is constructed which is drown by the Geolocating equation (3). Then, the probability of each selection of chromosomes is estimated. If the process of selection is satisfactory, the location of that chromosome is considered as the optimized solution. The satisfactory chromosome is which one that minimizes the value of the fitness function. Otherwise, roulette wheel selects new parents for new generation. This process is conducted by calculating cumulative distribution function (CDF) and make new generation as mating pool to be mutated. Mutation process is performed by a function to create new chromosomes as new potentiated source solutions. This step utilizes natural mutation coding method. Input variables for this function include new made population, mutation probability, decision variables and scaling parameter.

By adding these values to chromosomes which want to be mutated, some of its genes will swapped to create new generation. This process is continued to minimize fitness function which leads to the optimized solution (i.e. correct position).

3. Simulation

Simulations were performed to evaluate the performance of the proposed algorithm using

MATLAB 2014 on an Intel(R) Core(TM) i7 CPU at 2.93 GHz, with 4 GB of RAM. The procedure of simulation has been shown in figure (5).

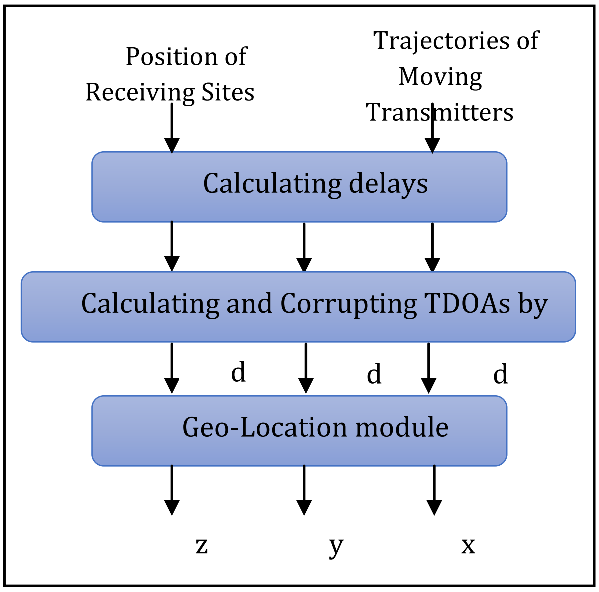


Figure 5: Description of the simulation and evaluation procedure.

In the first step, the topology of Geolocation problem was simulated consists of positions of receivers and trajectories of moving transmitters. The second stage belonged to computing TDOAs followed by corrupting them by measurement and asynchronous noises. Finally, the resultant TDOAs were been fed to Geolocating module to estimate the trajectories of transmitters. Table (1) shows the specifications of the simulated trajectories and the examined EC algorithms. As mentioned before, two members of evolutionary computation family (i.e. BA, GA) have been utilized in Geolocating module to represent the ability of this paradigm in position estimation. Furthermore, ML algorithm has been utilized as a representative for traditional methods to compare with EC techniques.

3.1. Tests and Results

Figure (6) shows the original simulated trajectories and their relative positions to receiver sites.

In the real situations, receivers always are not as same types and they are not calibrated actually, therefore TDOA noises are not negligible. To simulate this phenomenon firstly the measurement noises were added to simulated delays as the certain percent of them. The obtained corrupted delays have been fed to Geolocating module to estimate the trajectories of signal emitters. Figure (7) shows the trajectories which have been obtained from three examined methods in the presence of such noisy delays.

Table 1
Specifications of Simulation Scenario

Trajectory specifications	EC specifications	
	BA	GA
Number of Trajectories: 4	*Number of bees (n): 250*	*Number of chromosomes: 250*
Number of frames: 440(4×110)	*Number of scout bees: 25% of n*	*Scaling factor: 0.1*
Delay noise range: [0 80] microseconds	*Number of selected bees: 70% of n*	*Mutation possibility: 0.1*
Number of variables: 3	*Number of elite sites bees: 30% of n*	*Selection method: Roulette wheel*
Receivers positions(km): P_1=[200,205,7] p_2=[-190,190,7.5] P_3=[-200,-180,9] p_4=[190,-185,9.5]	*Number of iterations: 500*	*Iteration: 500*

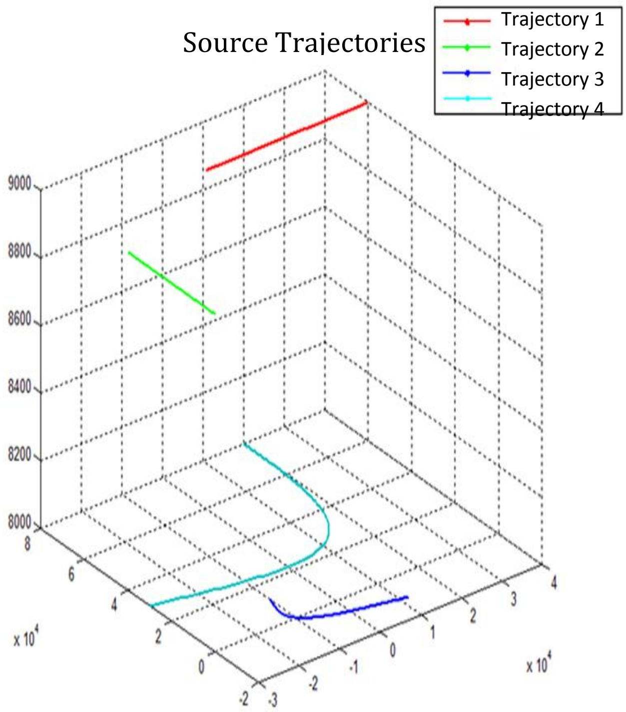
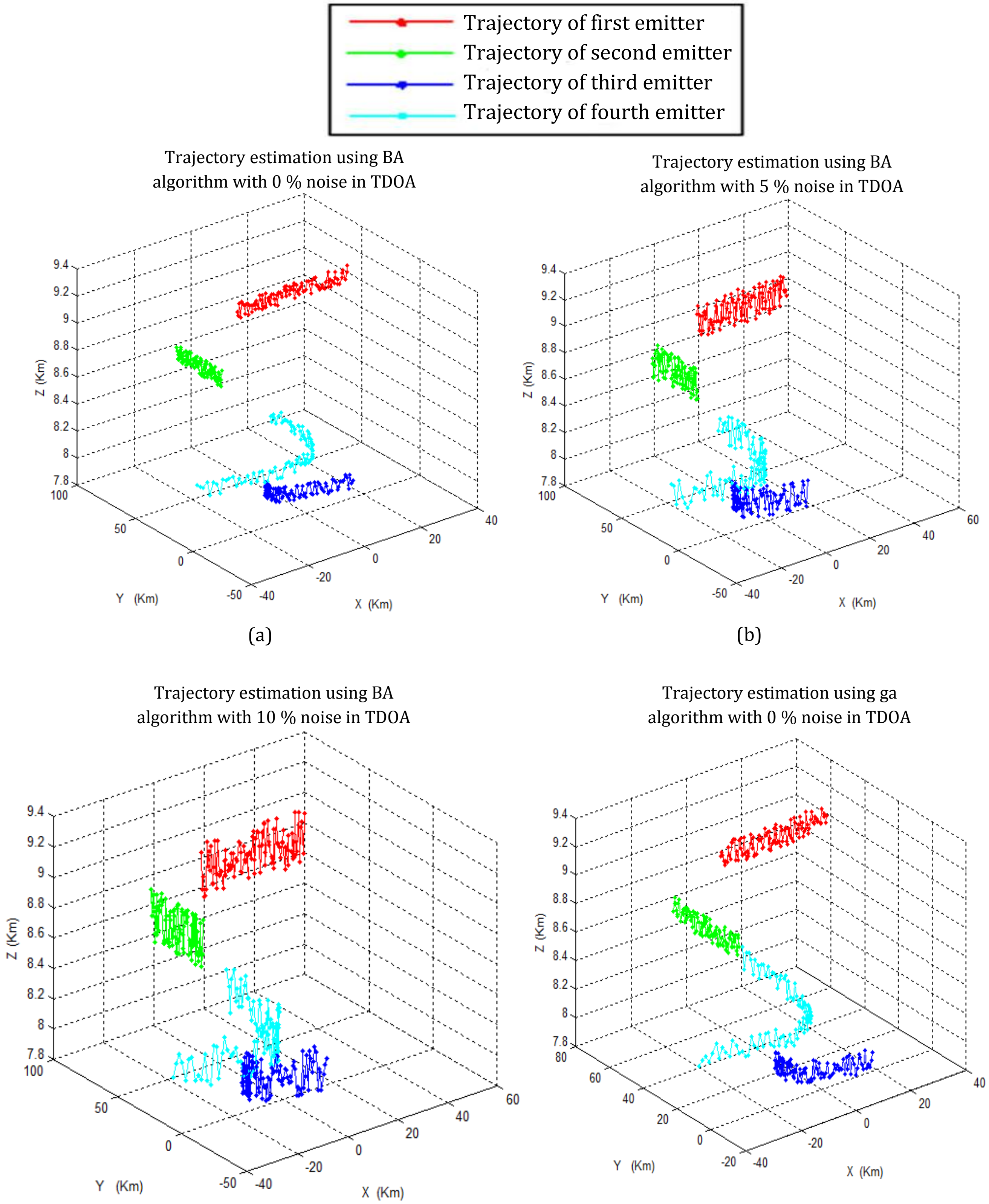


Figure 6: Illustration of four trajectories as original source positions.

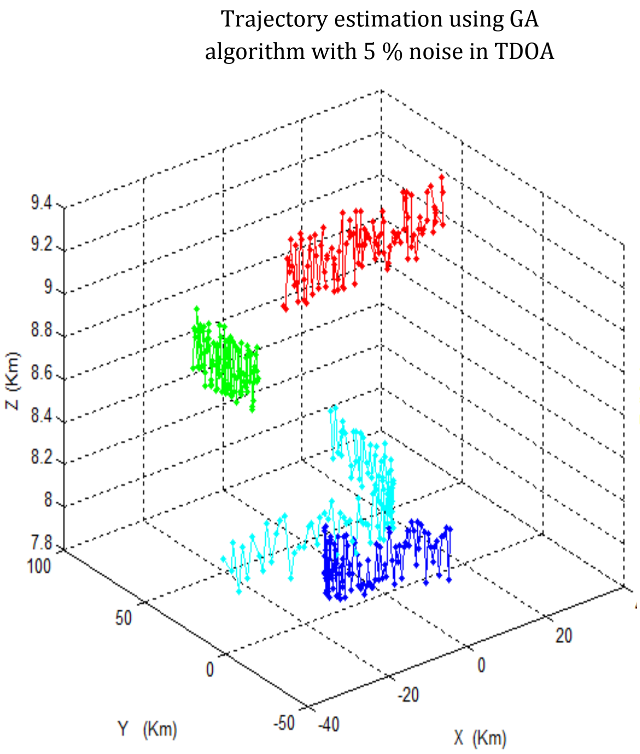
By exploiting the obtained graphs which are shown in Figure (7), it is observed that the trajectories obtained by using BA have lower fluctuations than those obtained by applying GA and ML.

Table (2) shows the mean errors assigned to each emitter in three directions as Δx_s Δy_s Δz_s which are obtained for the examined methods in presence of three different noise levels.

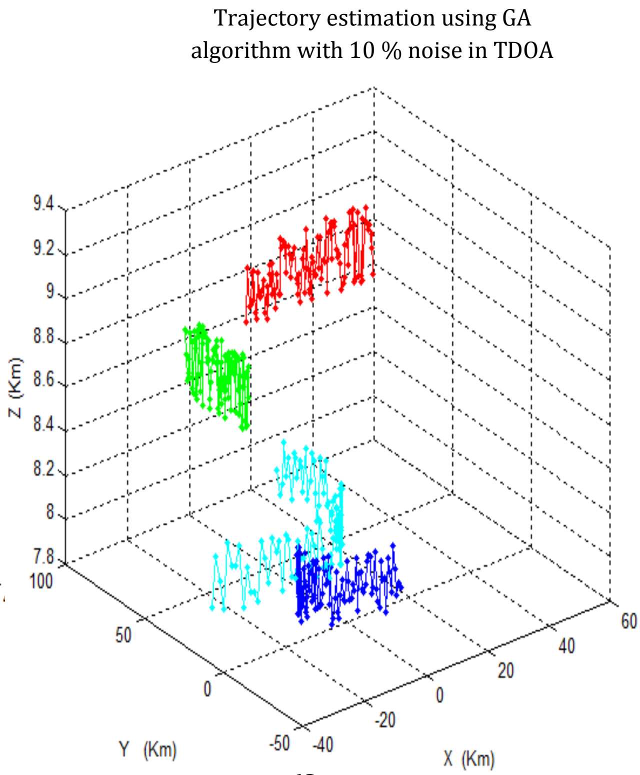

Trajectory of first emitter
Trajectory of second emitter
Trajectory of third emitter
Trajectory of fourth emitter
Trajectory estimation using BA algorithm with 0 % noise in TDOA
Trajectory estimation using BA algorithm with 5 % noise in TDOA
Trajectory estimation using BA algorithm with 10 % noise in TDOA
Trajectory estimation using ga algorithm with 0 % noise in TDOA
Z (Km)
Y (Km)
X (Km)

(a) (b)

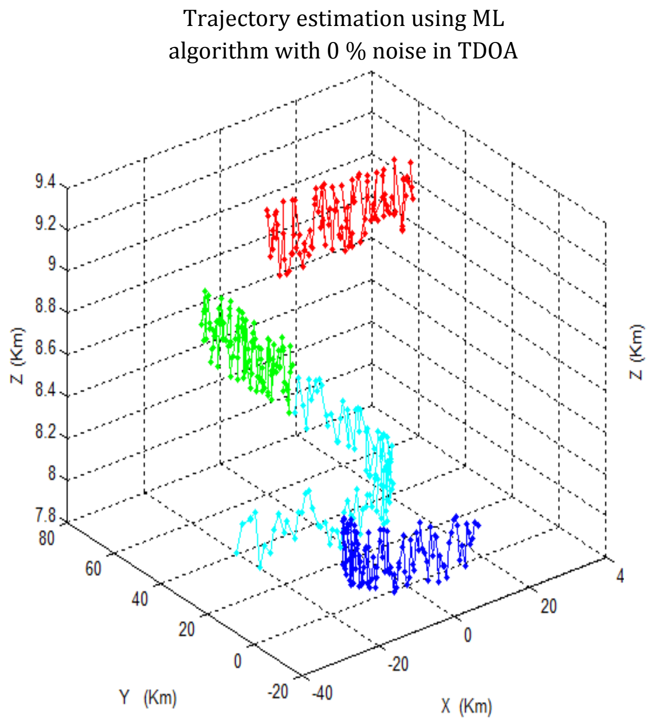
(c) (d)


Trajectory estimation using GA
algorithm with 5 % noise in TDOA
Z (Km)
Y (Km)
X (Km)

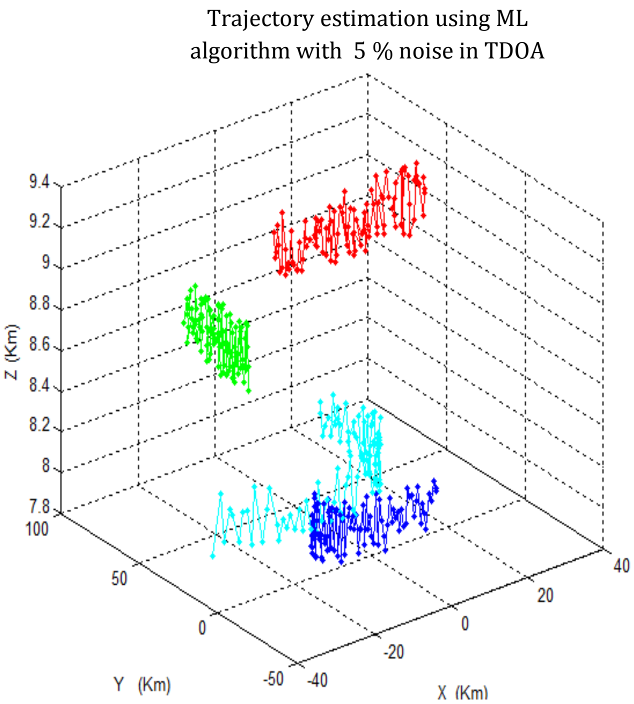
(e)


Trajectory estimation using GA
algorithm with 10 % noise in TDOA
Z (Km)
Y (Km)
X (Km)

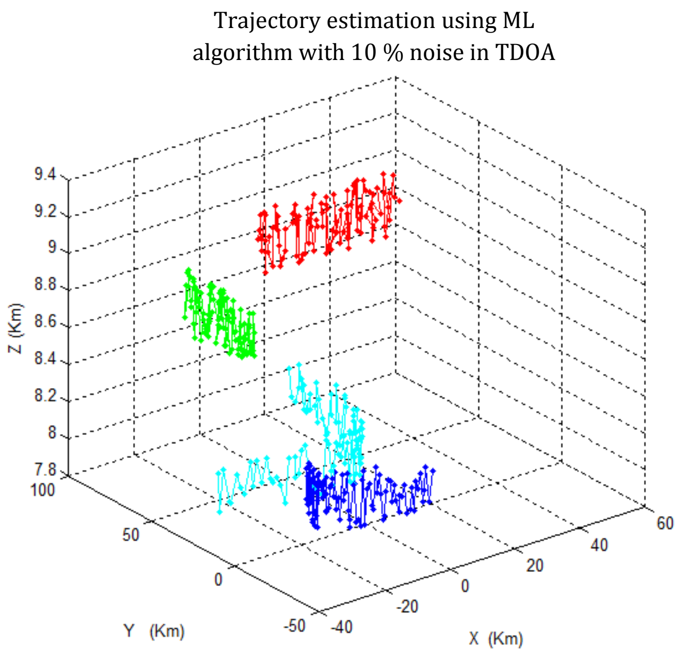
(f)


Trajectory estimation using ML
algorithm with 0 % noise in TDOA
Z (Km)
Y (Km)
X (Km)

(g)


Trajectory estimation using ML
algorithm with 5 % noise in TDOA
Z (Km)
Y (Km)
X (Km)

(h)



(i)

Figure 7: Estimation results in the presence of three levels of noises. Figures (a, b, c) show BA results in 0%, 5% and 10% level of noises respectively. Figures (d, e, f) and (g, h, i) are related to GA and ML results in presence of the above mentioned noises, respectively.

This table demonstrates when noise level is almost zero, although the BA algorithm achieves to the best results, but its errors are a bit (i.e. at least [0 1 87] meters) lower than GA and at least [41 27 37] meters lower than ML. By increasing noise level up to 5%, the superiority of the BA become considerable, in such way that its errors are at least [100 101 33] meters lower than GA and at least [353 305 58] meters lower than ML. By increasing the noise level up to 10%, the results of BA is still better than both of its alternatives. In this case, the BA defeates GA by obtaining errors [377 480 79] meters lower than those errors obtained by using it. In this case, the BA error is at least [629 634171] meters lower than those obtained by ML. the results show that GA method offers reliable results despite of this fact that its performance is a bit lower than BA method. Furthermore, it is comprehended that ML has reasonable results just in low levels of noise.

It is also notable that the lowest superiority belonged to estimation of height (i.e. Δz_s).

4. Analysis and Interpretation

As discussed in the previous section, the delay noise is the most important factor which determines the performance of Geolocation algorithms. Based on this fact, in this section, the sensitivity of the proposed algorithm and its alternatives are obtained against the delay noise.

For this purpose, the radial distances are estimated for all trajectories in spherical coordinate system. These estimations are performed in the worst case (i.e., 10% of noise in TDOA) and the resultant radial distances are compared to radial distances belonged to original trajectories (i.e. so called range error). Figure (8-a) shows how these range errors between real and estimated trajectories are changed versus different delay noises when the BA is utilized for Geolocation. In similar manner, Figures (8-b) and (8-c) shows the sensitivity of GA and ML versus delay noise for the same simulated trajectories.

These figures demonstrate that in low levels of delay noise the range error which are obtained by using BA are considerably lower than those which obtained by its alternatives.

For example, as indicated by markers in Figure (8), in the presence of delay noise equal to approximately 15, the obtained range error in estimating 4th trajectory is reached about 1.7 km for BA. In the same situation, the trajectories which are estimated by using GA and ML are about 1.9 km far from their exact locations, respectively. By increasing delay noise level up to approximately 45 μs , the estimated range is obtained 3.9 km far from exact location of emitter for the same trajectory by using BA. In this case, the obtained errors are about 4.2 km and 4.3 km by using GA and ML respectively.

TABLE2
COMPARISON OF PERFORMANCES OF THE EXAMINED ALGORITHMS IN PRESENCE OF THREE LEVELS OF NOISES

Noise Level	Error of Geo-locating by using BA (meters)	Error Geo-locating by using GA (meters)	Error of Geo-locating by using ML (meters)
	Δx_s Δy_s Δz_s	Δx_s Δy_s Δz_s	Δx_s Δy_s Δz_s
0	E_1 [0.36 0.36 309.36]	E_1 [9.6 8.65 502.31]	E_1 [42.27 36.2 621.32]
	E_2 [2.36 1.98 405.74]	E_2 [7.65 3.36 492.55]	E_2 [52.75 100.1 442.23]
	E_3 [0.45 1.86 340.47]	E_3 [0.3 3.36 522.43]	E_3 [62.34 40.1 525.28]
	E_4 [0.10 2.34 307.36]	E_4 [4.32 5.37 592.8]	E_4 [45.47 30.08 530.20]
5%	E_1 [236.35 153.37 1253.36]	E_1 [426.35 398.91 1286.34]	E_1 [589.3 603.5 1942.23]
	E_2 [296.34 302.17 1223.84]	E_2 [396.84 498.64 1396.74]	E_2 [852.41 902.36 1496.65]
	E_3 [241.38 267.58 1243.81]	E_3 [452.77 562.87 1693.3]	E_3 [808.25 986.35 1396.34]
	E_4 [302.78 200.14 1391.12]	E_4 [408.4 301.25 1693.3]	E_4 [705.23 925.24 1449.64]
10%	E_1 [402.3 362.35 1552.77]	E_1 [925.34 865.78 1631.15]	E_1 [1210.1 996.6 1723.2]
	E_2 [321.3 430.2 1338.39]	E_2 [869.39 927.73 1826.2]	E_2 [1332.52 1151.35 1963.5]
	E_3 [496.35 363.35 1669.41]	E_3 [873.14 1024.98 1925.3]	E_3 [1125.36 1251.2 2031.3]
	E_4 [402.4 398.35 1484.82]	E_4 [911.28 878.81 1802.36]	E_4 [1253.3 1223.36 1989.3]

On the other hand, results show that by increasing delay noises the superiority of BA are still obvious against its alternatives.

Now, to analysis the superiority of BA against GA and ML, the mentioned range errors are accumulated for each trajectory which leads to its dedicated error. The obtained errors are averaged for all trajectories which are obtained by using each algorithm to perform the range error of that algorithm. Finally, range errors of GA and ML are compared to those one obtained by using BA in percent scale to evaluate the excellence of BA results against its alternatives. This procedure is performed in three different noise levels equal to 0%, 5% and 10% as shown in Figure (9). It may be shown that when noise level is almost zero, the results of BA are about 12% more accurate than GA and 21% better than that obtained by applying ML. BA have the ability of golobal searching on noisy conditions better than GA [25], therefore BA method has better results with high accuracy compared to GA [26]. It may be inferred from this figure that in the presence of greater amounts of noise the BA is still better than both of its alternatives but its superiorities are declined against GA while increased against ML. This superiority is only 4.5% better than the best method among its alternatives (i.e. GA) in the presence of noise up to 5% noise.

On the other hand, the excellence of BA versus GA is degraded to 3% in presence of 10% of noise. In parallel the excellence of BA against ML increased up to 33% and 30% in presence of 5% and 10% of TDOA noises, respectively.

5. CONCLUSION

In this paper a new method for Geo-locating emitters were introduced, which utilized evolutionary computation framework for robust solving of TDOA equations. For this purpose, Bees Algorithm (BA) and Genetic Algorithm (GA) were selected as representatives of EC paradigm and their performances were compared to Maximum Likelihood (ML) method as a delegate for existing traditional methods. The effectiveness of the proposed paradigm was demonstrated by performing simulation under a scenario which has been inspirited from real conditions, in such way that several linear and nonlinear moving emitters were simulated and their relevant TDOAs were corrupted by different amounts of measurement and asynchronous noises.

The obtained results showed that the EC paradigm has been able to Geolocate the simulated emitters even in the worst case (i.e. presence of 10% of TDOA noise) with errors at least 252, 131 and 92 meters lower than ML respectively in three Cartesian directions.

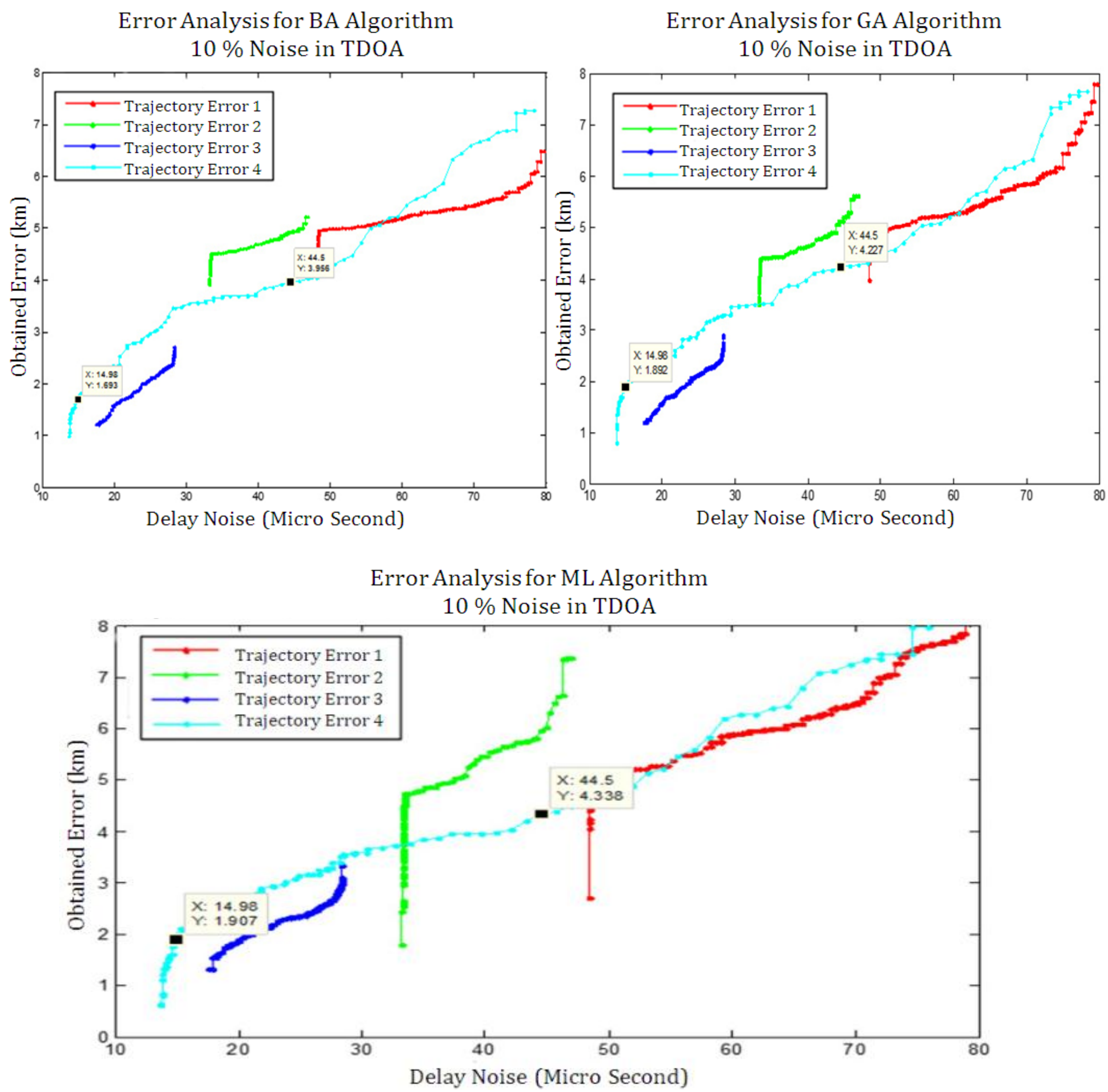


Figure 8: sensitivity of algorithms against the changes in delay noise in BA, GA and ML methods and exposed to three different levels of noises.

Furthermore, in EC paradigm, the BA method showed better performance than another simulated member of this family (i.e. GA) in all simulation conditions. The obtained results showed 12%, 4.5% and 3% of excellence for the obtained range error of BA against the same parameter for GA the in the presence of 0, 5 and 10 percent of noise, respectively.
methods may be considered as an actual solution for Geolocating, especially, in noisy environments.

The obtained results showed the effectiveness of the EC paradigm to increase the accuracy of TDOA Geo-locating of emitters; therefore, in parallel with the improvement of the speed of hardware this family of methods may be considered as an actual solution for Geolocating, especially in noisy environments.

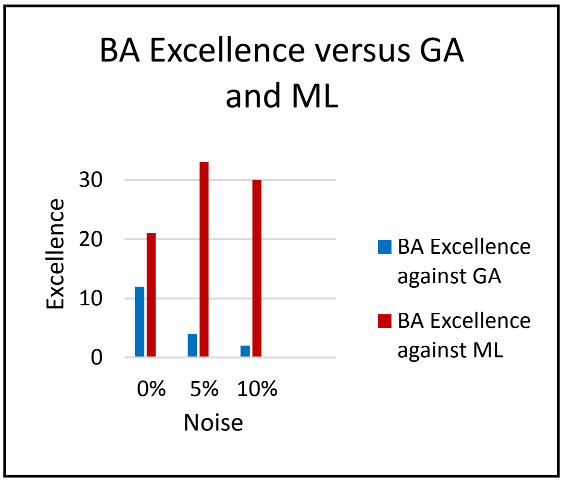


Figure 9: Performance comparison of BA in terms of range error against GA and ML in the presence of three examined noises.

REFERENCES

[1] M. A. Spirito and A. G. Mattioli, “On the hyperbolic positioning of GSM mobile stations,” in *Proc. 1998 international Symposium on Signals, Systems and Electronics, Conf,* Pisa, Italy, 1998.

[2] K. C. Ho and Y. T. Chan, “An asymptotically unbiased estimator for bearings-only and doppler-bearing target motion analysis,” *IEEE Trans. Signal Processing*, vol. 54, no. 3, pp. 809-822, Mar. 2006.

[3] G. C. Carter, “Time delay estimation for passive sonar signal processing,” *IEEE Trans. Acoust., Speech, Signal Processing*, vol. ASSP-29, no. 3, pp. 462–470, Jun. 1981.

[4] Y. T. Chan and J. J. Towers, “Passive localization from Doppler-shifted frequency measurements,” *IEEE Trans. Signal Processing,* vol. 40, no. 10, pp. 2594-2598, Oct. 1992.

[5] Y. T. Chan and K. C. Ho, “A simple and efficient estimator for hyperbolic location,” *IEEE Trans. Signal Processing*, vol. 42, no. 8, pp. 1905-1915, Aug. 1994.

[6] F. Evennou, F. Marx, and S. Nacivet, “An experimental TDOA UWB location system for NLOS environments,” in *Proc. IEEE 62 nd Vehicular Technology Conference-Fall*, *Conf.*, pp. 420-423, Dallas, TX, USA, 2005.

[7] R. Poisel, “Electronic warfare target location methods,” Boston:Artech House, 2005, p. 272.

[8] H. C. Schau and A. Z. Robinson, “Passive source localization employing intersecting spherical surfaces from time-of-arrival differences,” *IEEE Trans. Acoust., Speech, Signal Processing*, vol. ASSP-35, pp.1223-1225, Aug. 1987.

[9] S. Fischer, H. Koorapaty, E. Larsson, and A. Kangas, “System performance evaluation of mobile positioning methods,” in *Proc. 1999 IEEE Vehicular Technology, Conf.,* Houston, TX, USA, 1999.

[10] M. A. Spirito, “Further results on GSM mobile station location,” *IEEE Trans. Electronics Letters*, vol. 35, no. 11, pp. 867-869, May. 1999.

[11] D. Koks, “Numerical Calculations for Passive Geolocation,” Defence Science and Technology Organisation, Edinburgh, SA, Tech. Rep. AR-013-779, Jan. 2007.

[12] K. W. K. Lui, J. Zheng, and H. C. So, “Particle swarm optimization for time-difference-of-arrival based localization,” In Proc. 2007 of European Signal Processing Conference, Conf., p. 414-417, Poznan, Poland, 2007.

[13] G. Mellen, M. Pachter, and J. Raquet, “Closed-form solution for determining emitter location using time difference of arrival measurements,” IEEE Trans. Aerospace and Electronic Systems, vol. 39, no. 3, pp. 1056-1058, Jul. 2003.

[14] B. T. Fang, “Simple solutions for hyperbolic and related position fixes,” *IEEE Trans. Aerosp. Electron. Syst.*, vol. 26, pp. 748-753, Sept. 1990.

[15] B. Friedlander, “A passive localization algorithm and its accuracy analysis,” *IEEE J. Ocean. Eng.*, vol. OE-12, pp. 234-245, Jan. 1987.

[16] O. Smith and J. S. Abel, “Closed-form least-squares source location estimation from range-difference measurements,” *IEEE Trans. Acoust., Speech, Signal Processing*, vol. ASSP-35, pp.1661-1669, Dec. 1987.

[17] J.S. Abel and J. O. Smith, “The spherical interpolation method for closed-form passive source localization using range difference measurements,” in Proc. ICASSP-87, pp. 471-474, Dallas, TX, USA, 1987.

[18] W. H. Foy, “Position-location solutions by Taylor-series estimation,” *IEEE Trans. Aerosp. Electron. Syst.*, vol. AES-12, no. 2, pp. 187-194, Mar. 1976.

[19] D. J. Torrieri, “Statistical theory of passive location systems,” *IEEE Trans. Aerosp. Electron. Syst.*, vol. AES-20, pp. 183-198, Mar. 1984.

[20] R. C. Eberhart and Y. H. Shi, “Particle swarm optimization: developments, applications and resources,” in *Proc. 2001 IEEE Congress on Evolutionary Computation*, pp. 81-86, Seoul, South Korea, 2001.

[21] E. Bonabeau, M. Dorigo, and G. Theraulaz, “Swarm intelligence: from natural to artificial systems,” New York: Oxford University Press, 1999, pp. 320.

[22] S. Camazine, J. Deneubourg, N. R. Franks, J. Sneyd, G. Theraula, and E. Bonabeau, “Self-Organization in Biological Systems,” Princeton: Princeton University Press, 2003, pp. 560.

[23] G. Bilchev and I. C. Parmee, “The ant colony metaphor for searching continuous design spaces,” AISB Workshop Sheffield on Evolutionary Computing, 1995, pp. 25-39.

[24] T. D. Seeley, “The wisdom of the hive: the social physiology of honey bee colonies,” Massachusetts: Harvard University Press, Cambridge, 1996, p. 318.

[25] B. Yuce, M. S. Packianather, E. Mastrocinque, D. T. Pham, and A. Lambiase, “Honey bees inspired optimization method: The bees algorithm,” *Insects*, vol. 4, pp. 646-662, 2013.

[26] P. Curkovic and B. Jerbic, “Honey-bees optimization algorithm applied to path planning problem,” *Int. J. Simul. Model*, vol. 6, pp. 154-164, 2007.

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