A Hybrid Algorithm of Source Localization Based on Hyperbolic Technique in WSN

Homayun Kabir[1*], Jeevan Kanesan[1], Ahmed Wasif Reza[1], Harikrishnan Ramiah[1]

[1]Faculty of Engineering, Department of Electrical Engineering, University of Malaya, 50603 Kuala Lumpur, Malaysia.
hkabir.um@siswa.um.edu.my
hkabir.um@siswa.um.edu.my, jievan@um.edu.my, wasif@um.edu.my, and hrkhari@um.edu.my

Abstract**:** Electromagnetic (EM) source localization has become a vital issue lately to improve civilian safety, increase the military security and mitigate the disaster effect. The localization is embedded in battle-field surveillance, traffic alert, emergency call 911 (E911), resource allocation and mitigation of disaster effect. The location of the emitter can be determined by bestowing its transmitted signal measured at an array of spatially separated receivers. Several methods have been developed for estimating the EM source location. These methods include Time of Arrival (TOA), Time Difference of Arrival (TDOA), Frequency Difference of arrival (FDOA), Angle of Arrival (AOA) and Received Signal Strength (RSS) of the transmitted emitter signal. Comparing all localization techniques, TDOA and FDOA localization techniques (hyperbolic) are one of the simplest and most cost effective. The sensors situated on an axis in two-dimensional scenario measuring the TDOA and FDOA of the emitting signal from a moving source can estimate its position and velocity from the intersection point of hyperbola, which is created from TDOA and FDOA non-linear equations set. However, the hyperbolas may not be intersected at a single point due to the non-linear localization equations set and measurement noise in wireless sensor network (WSN). It is therefore important to estimate a source position that minimizes its deviations from the actual position. In this paper, a hybrid method combined with maximum likelihood (ML) and genetic algorithm (GA) are proposed to determine the instantaneous position of the moving source by estimating the position and velocity based on hyperbolic techniques (TDOA and FDOA). Firstly ML is applied in the position and velocity localization data. Additionally, GA is implemented to acquire the globally best solution of localization parameters from non-linear equations set of ML solution. The results obtained confirmed that the proposed method achieved the theoretical lower bound for near to far-field with same and different velocity and different baseline of sensors in low to high Gaussian noise level. In this study, explicit solutions are provided by the proposed methods that are not achievable through the established methods in all cases.

Keywords**:** Localization, Hyperbolic Technique, Maximum likelihood, Genetic Algorithm**.**

1. Introduction

Electromagnetic (EM) sources are an important part of civilian and military applications. However, sometimes technology, which relates to EM sources, is misused. For leading a better life, localization awareness plays a pivotal role in civilian and military applications. Localization systems have emerging civilian and military applications. Examples include, but not limited to battlefield command and control [1], fire fighters tracking [2], emergency 911 (E911) [3], collision avoidance in multi-robot system [4] and road traffic control [5], resource allocation [6], routing [7] in sensor networks, etc. The location of the emitter can be detected by utilizing its transmitted signal measured at an array of spatially separated receivers called wireless sensor network (WSN). Time of Arrival (TOA) [8], Time different of Arrival (TDOA) [9], Angle of Arrival (AOA) [10] and Received Signal Strength (RSS) [11] of the transmitted signal from the emitter are usually utilized for locating the emitter. The information about the distance between the receiver and sensor is directly provided by TOA, TDOA and RSS. The AOA contributes for getting the source bearing relative to the sensors. TOA and TDOA are used to determine the location of emitter using arrival time of the signal at the receiver which comes from the emitter. The AOA technique is used to measure the arrival angle of the signal from the emitter to sensors. The signal strength of the sensor is utilized by RSS technique. The main drawback of RSS technique is that it is difficult to pick up the approximate received signal by sensors [11]. An important drawback of AOA technique is that specialized receiver is required to measure the arrival angle of the received signal. Still now, the design of a special receiver for AOA and time synchronization system is difficult which made its implementation not easy [12]. In TOA based localization, the signal transmitting time of the source is required to calculate the source location parameters. Time synchronization with GPS is also a drawback in TOA [13]. Among the above techniques, TDOA is most feasible due to passive localization, which does not have necessarily time-stamping and therefore, easy to execute in the real-world localization experimental set up [14]. For moving emitter, application of Doppler theory called frequency difference of arrival (FDOA) is utilized to calculate the velocity combined with TDOA [15]. Still now, some limitation is faced to locate the position and the velocity of moving emitter which are i) inconsistency problem when more than two for 2-D TDOA and FDOA measurement are available, ii) Non-linear relation between source and sensors position creates the challenges and iii) Localization geometry of WSN. Therefore, the main challenge of localization is minimizing the deviation between the actual and estimated the position and velocity of moving emitter. One of the best powerful tools to solve localization estimation problem is maximum likelihood (ML) technique. But, direct approach that uses the ML estimation to solve this problem is exhaustive search in the solution space [16]. Some researchers have developed closed form linear techniques, which can give optimum location estimates only for low to moderate noise [16-19]. For overcoming these challenges, including low to high noise level, we have proposed a hybrid algorithm combined with ML and genetic algorithm (GA) based on hyperbolic technique to estimate the position and velocity of a moving source in WSN. Here, GA is applied to acquire the globally best solution of localization parameters from non-linear equation sets of ML solution. In this paper, we simulated hybrid method to estimate the position and velocity of moving source at near and far filed, where Gaussian noise is considered.

This paper is arranged in the following manner. In the following section, the hybrid method is presented. Next, the derivation of Cramer-Rao Lower Bound (CRLB) is provided. After that, the results are analyzed and performance evaluation is explained. Finally, the conclusion is presented.

2. Proposed Method

The *N* receivers of WSN are assumed in 2-D space to calculate the moving source with unknown the position $p=[x\ \ y]^T$ and velocity $v=[v_x\ v_y]^T$ using the hyperbolic localization approach, where matrix transpose operation is symbolized by *T*. The emitted signals from the emitter are received by *N* receivers of WSN, which are located at $R_i=[x_i\ y_i]^t$ with the velocity $u_i=[u_{xi}\ u_{yi}]^T$, where $i=1, 2, 3,\ldots, N$. The distance between the i^{th} receiver and source is,

$$d_i^0=|p-R_i|=\sqrt{(p-R_i)^T(p-R_i)} \tag{1}$$

The true range difference of receiver pair i^{th} and reference that considered sensor 1 is,

$$d_{i1}^0=ct_{i1}=d_i^0-d_1^0 \tag{2}$$

In terms of equation (2), the signal propagation velocity is *c* and the time difference of receiver pair i^{th} and reference is t_{i1}. The equation (2) is a non-linear set with unknown *p*, that creates *N*-1 hyperbolic curves with focus $R_i=[x_i\ y_i]^t$ where $i=1,2,3,\ldots, N$. Those hyperbolic curves intersect at a point that provides the predictable position of the emitter. Minimum two hyperbolic curves are mandatory to resolve the localization problem by exploiting the TDOA in the 2-D scenario.

Not only the position but also the velocity estimation is important for estimating the position and the velocity of moving source. Conversely, TDOA equations set may be inadequate to provide the needed localization accuracy of moving source as TDOA calculates only the position of the source. The FDOA technique that is acquired from the relative velocity between the sensors [15] and emitter, is applied to improve instantaneous localization accuracy of the emitter. The relation between the distance rate and emitter position and velocity parameters is derived from the time derivative of the equation (1) as follows:

$$v_i^0=\frac{(v-u_i)^T(p-R_i)}{d_i^0} \tag{3}$$

The FDOA is measured by the time derivative of the equation (2) as follows:

$$v_{i1}^0=v_i^0-v_1^0 \tag{4}$$

In terms of equation (4), the range difference rate is denoted by v_{i1}^0 that is acquired from FDOA. The unknown position p and velocity v of the emitter are determined by resolving the obtained TDOA and FDOA equations set [20].

The path and path rate measurements between the sensors and emitter are linearly correlated with the TOA measurements. EM waves transmit through different kind of mediums while traveling along the pathway from a source to a sensor. The velocity of EM waves is constant due to the obstructed range length is much smaller than the traveling distance in the air. For representing the practical environment, noise can be divided into two sections namely; line of sight (LOS) and non-line of sight (NLOS). The true path difference and path difference rate measurements from the source to the receivers are affected with only the standard measurement noise if there is a complete LOS. This measurement noise is supposed to have a distribution that is almost similar to the Gaussian distribution, but with the fine support region. In this paper, we have focused our research to calculate the position and the velocity of emitter considering only LOS noise. Therefore, the path difference and path difference rate measurements of the position localization technique are modeled as follows:

$$d_{i1}=d_{i1}^0+n_{i1} \tag{5}$$

$$v_{i1}=v_{i1}^0+nv_{i1} \tag{6}$$

Here, n_{i1} and nv_{i1} are additive white Gaussian noise. Hence, $D=[d_{21}\,d_{31}\ldots d_{N1}]$ and $V=[v_{21}\ v_{31}\ldots v_{N1}]$ are the vector of noisy TDOA and FDOA that have a covariance matrix [17, 21].

$$Q=E\{[D^T\ \ V^T]^T[D^T\ \ V^T]\}=\sigma^2\begin{bmatrix}Q_1 & \mathrm{O}\\ 0 & \mathrm{Q}_1\end{bmatrix} \tag{7}$$

Here, the variance of zero mean Gaussian noise is σ^2 and **0** is a zero square matrix.

$$Q_1=\begin{bmatrix}1 & 0.5 & 0.5 & . & . & . & 0.5\\ 0.5 & 1 & 0.5 & . & . & . & 0.5\\ 0.5 & 0.5 & 1 & . & . & . & 0.5\\ . & . & . & . & . & . & .\\ . & . & . & . & . & . & .\\ . & . & . & . & . & . & .\\ 0.5 & 0.5 & 0.5 & . & . & . & 1\end{bmatrix}$$ which is a $(N\text{-}1)\times(N\text{-}1)$ matrix.

An auxiliary vector that comprised of the unknown position and velocity parameters of moving emitter is defined as $\alpha=[p\ \ v]^T$, the noisy TDOA and FDOA data is $[D\ V]^T$. The probability density function (PDF) of $[D\ V]^T$ given by as [22]

$$([D^T\ V^T]^T/\alpha)=(2\pi)^{-\frac{N}{2}}(\det(Q))^{-\frac{1}{2}}\exp\{-\frac{j_1}{2}\} \tag{8}$$

After simplification $J_1(\alpha)$ can be denoted as

$$J_1(\alpha)=\sum_{i=2}^{N}((d_{i1}-d_{i1}^0)^2+(v_{i1}-v_{i1}^0)^2) \tag{9}$$

The auxiliary vector of the position and velocity of the moving source can be obtained by utilizing the optimization process into equation (9). A GA is a search heuristic that mimics the process of natural evolution. This heuristic is routinely used to generate useful solutions to optimization and search problems. GA belong to the larger class of evolutionary algorithms, which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover [23, 24]. Hence, GA is one of the best methods to do the global optimization [25, 26]. Thereby, we have applied the GA to find out the best approximation of auxiliary vector. A simple GA procedure has been stated as follows:

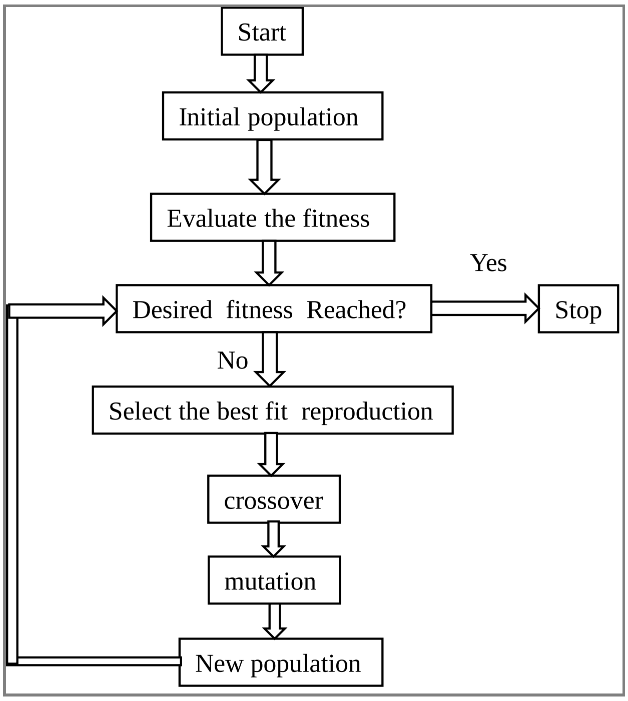


Figure 1: Block Diagram of simple GA

2.1. Initialization

GA is essentially unique in relation to the optimization algorithm. A GA is a probabilistic system that has established the standards of genetics. In this system the first style is to depict the length of the genetic string named Chromosome. These Chromosomes having a quality of the destination role are termed as Chromosome's fitness. After selecting the length of Chromosome, the initial samples of the Chromosome relies on the arbitrary collection of a number of chromosomes.

In this suggested issue, to determine the values of parameter the position *p* and the velocity *v* of moving source in WSN was applied which permitted maximizing the value of J_1. For optimizing the non-linear equations set of moving source localization in WSN, the GA is designed as follows: the construction of the Chromosome is 30 bits separated into four genes *G1, G2, G3* and *G4* presenting position *p* and velocity *v* of moving source in the 2-D scenario, respectively where *p* (position coordinates of source) and *v* (velocity coordinates of source) are initialized by ±20% of actual values of *p* and *v*. As an example, two binary strings of the Chromosomes are B1 and B2 where,

B1= 1 0 1 1 0 1
B2= 0 1 1 0 1 0

Based on the fitness of individual population, a probabilistic choice is made at this stage.

2.2. Crossover

The genetic operator is utilized after the determination operation for generating new results depending on the current results in the sample. Two sorts of essential specialists can be found, one is a crossover and another is mutation. The input of the crossover operation is a couple of Chromosome called Guardians and the output gives a reproduced Chromosome known as Children. Sets associated with individuals were picked up arbitrarily from the mating pool according to the probability of crossover. Provided that the parallel letter set was utilized within GA then every spot was given transformation probability from 0 to 1. The variation in the quality is generally low.

The crossover is done in two steps for selected two Chromosomes. 1) The samples are represented by the binary strings 2) according to the probability distribution, two Chromosomes do crossover in which binary strings can be switched. Therefore single point crossover and two point crossover are used for these Chromosomes. By using uniform probability distribution the crossover point is chosen. As an example, if 5 is the crossover site, the aforementioned B1 and B2 is changed after the first step crossover and A1 and A2 will be

S1= 1 0 1 1 <u>1 0</u>
S2= 0 1 1 0 <u>0 1</u>

The sample uses the uniform crossover in the first step. In this step 2 binary strings are created and the common terms are searched in both parents, to find out the common mark the common terms. In the string template, the binary bit will be set to 1 when there is matching term in both parents, otherwise it will be zero. Again from the population two numbers are selected randomly and exchanged with each other. As an example, if M1 and M2 are the set of random number as

M1= 9 13 15 14 20 17 11
M2= 21 17 11 12 15 19 10 13 16

And these M1 and M2 is made crossover with B1 and B2, the two parents Chromosomes are changed after the first step crossover. The new children will be like as
T1= 1 0 1 1 1 0 9 13 15 14 20 17 11
T2= 0 1 1 0 0 1 21 17 11 12 15 19 10 13 16

Second step crossover is done to increase the diversity and the new Chromosomes becomes
T1= 1 0 1 1 1 0 <u>21 17 11 12 15 19 10 13 16</u>
T2= 0 1 1 0 0 1 <u>9 13 15 14 20 17 11</u>

Within GA to reach the very least or perhaps greatest position in search engine optimization, progress as well as procedure of selection is usually duplicated. When the fitness of the best Chromosome does not change significantly, the

GA operation is finished.

2.3. Mutation

Changing a small number of bases randomly with small probability is known as mutation. It is performed for maintaining the diversity in the population. To avoid the parameter convergence this operation is essential. The proper convergence of the GA is dependent upon its configuration which is a very important issue. This convergence is made by defining the control parameters like the population size, the Chromosome size, mutation rate and crossover point. Unfortunately, it is a very difficult task to determine these parameters and in most of the cases, they are defined empirically. From the population, for each selected Chromosome was mutated separately, like the crossover. The operator exchanges with a randomly selected term in the corresponding complimentary subset of the string. In this case a simple point mutation is used. As an example, after mutation T1 will be as follows:

T1= 1 0 0 10 17 11 12 15 19 48 13 16

Parameters for the genetic algorithm configuration were:

- Size of the population: 800
- Rate of Mutation: 0.25%
- Stopping Criteria: 300

3. Theoretical Lowed bound

It is important to know the optimum achievable localization accuracy that can be attained with the available measurement set. The CRLB is the theoretical limit for the variance of the estimator's output. It provides a lower bound on the covariance that is asymptotically achievable by any unbiased estimation algorithm [27]. Therefore, the CRLB sets a benchmark against which the performance of an unbiased estimation is compared [17, 28]. The CRLB of moving source in WSN is equal to the inverse the Fisher matrix that is defined as [17]

$$J = E[(\frac{\partial Inp(F;\beta)}{\partial \beta})^T (\frac{\partial Inp(F;\beta)}{\partial \beta})]_{\beta=\beta_0} \tag{10}$$

In terms of equation (10), the vector of distance and distance rate differences is $F = [d_{21}d_{31}d_{41}...d_{(N-1)1}, v_{21}v_{31}v_{41}...v_{(N-1)1}]^T$, β is the parameterized vector of TDOA and FDOA localization technique. In addition, $p(F;\beta)$ is the Gaussian distribution with mean $p^0(\beta)$ and covariance matrix **Q**. The desired CRLB of moving source for WSN is obtained after taking log and performing differentiation as follows:

$$CRLB(\beta) = \{((\frac{\partial p^0(\beta)}{\partial \beta})^T Q^{-1} (\frac{\partial p^0(\beta)}{\partial \beta})_{\beta=\beta_0}\}^{-1} \tag{11}$$

The equation (11) can be represented as

$$\frac{\partial p^0(\beta)}{\partial \beta} = \begin{bmatrix} \frac{\partial D^0(\beta)}{\partial p} & \frac{\partial D^0(\beta)}{\partial v} \\ \frac{\partial V^0(\beta)}{\partial p} & \frac{\partial V^0(\beta)}{\partial v} \end{bmatrix} \tag{12}$$

where $D^0 = [d_{21}^0\, d_{31}^0 ...\, d_{N1}^0]^T$, $V^0 = [v_{21}^0\, v_{31}^0 ...\, v_{N1}^0]^T$, and $p^0(\theta) = [D^{0T}\; V^{0T}]^T$.

We obtained from equation (1)

$$d_{i1}^0 = |\, p - R_i \,| - |\, p - R_1 \,| \tag{13}$$

From equation (3), the equation (13) can be obtained.

$$v_{i1}^0 = \frac{(v-u_i)^T (p-R_i)}{d_i^0} - \frac{(v-u_1)^T (p-R_1)}{d_1^0} \tag{14}$$

Applying the partial derivation of d_{i1}^0 and v_{i1}^0 with respect to *p* and *v* yields in equation (15) to (18)

$$\frac{\partial D^0}{\partial p} = \begin{bmatrix} \frac{(p-R_2)^T}{d_2^0} - \frac{(p-R_1)^T}{d_1^0} \\ . \\ . \\ \frac{(p-R_N)^T}{d_N^0} - \frac{(p-R_1)^T}{d_1^0} \end{bmatrix}_{(N-1)\times 3} \tag{15}$$

$$\frac{\partial D^0}{\partial v} = 0_{(N-1)\times 3} \tag{16}$$

$$\frac{\partial V^0}{\partial p} = -\begin{bmatrix} \frac{(p-R_2)^T v_2(\beta)}{d_2^{0^2}} - \frac{(p-R_1)^T v_1(\beta)}{d_1^{0^2}} - \frac{(v-u_2)^T}{d_2^0} + \frac{(v-u_1)^T}{d_1^0} \\ . \\ . \\ \frac{(p-R_N)^T v_N(\beta)}{d_N^{0^2}} - \frac{(p-R_1)^T v_1(\beta)}{d_1^{0^2}} - \frac{(v-u_N)^T}{d_N^0} + \frac{(v-u_1)^T}{d_1^0} \end{bmatrix} \tag{17}$$

$$\frac{\partial V^0}{\partial v} = 0_{(N-1)\times 3} \tag{18}$$

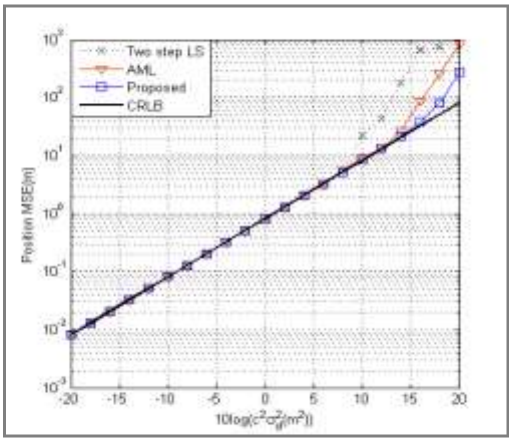
Substituting the all necessary value from equation (15) to (18), into equation (11), the CRLB for moving emitter based on hyperbolic technique is obtained.

4. Result and Discussion

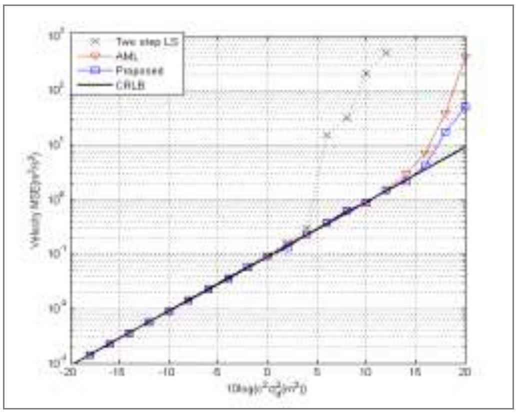
In this section, the computational simulations using the MATLAB have been executed to evaluate the performance of the proposed hybrid method, Two step LS [17] and AML [16] contrasted with CRLB in WSN, where, Gaussian noise was considered as $dB = 10\log(\sigma^2)$. The mean square error (MSE) of the proposed method (hybrid) is calculated via $MSE_p = \sum_1^M \| p - p^0 \|^2 / M$ and $MSE_v = \sum_1^M \| v - v^0 \|^2 / M$ for position and velocity of the moving source where *M=1E5* is the quantity of random generation to maintain the covariance of Gaussian noise. In regards to MSE equation, p^0 and v^0 are the actual source position and velocity, besides, *p* and *v* are the estimated position and velocity of CRLB or proposed hybrid method or two step LS or AML. The true position p^0 emitters were A (8m, 22m) and B (-50m, 250m) for near and far field where the velocity v^0 was (-2m/s, 1.5m/s) for both cases [29]. In addition, the moving sensor's position and velocity were shown in Table 1.

Table 1: Position and velocity coordinates of sensors in WSN

No. of sensor	$x_i(m)$	$y_i(m)$	$v_{xi}(m/s)$	$v_{yi}(m/s)$
1	30	10	3	-2
2	40	15	-3	1
3	30	50	1	-2
4	35	20	-1	1
5	-10	-10	-2	1



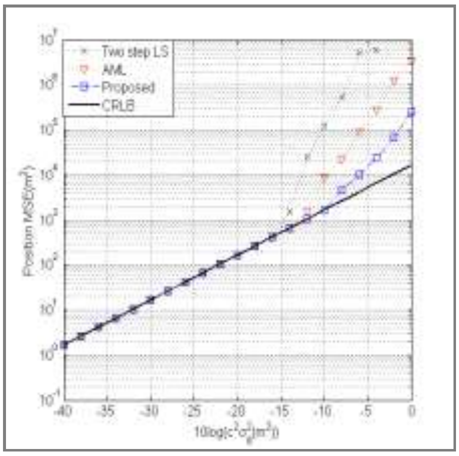
(a)



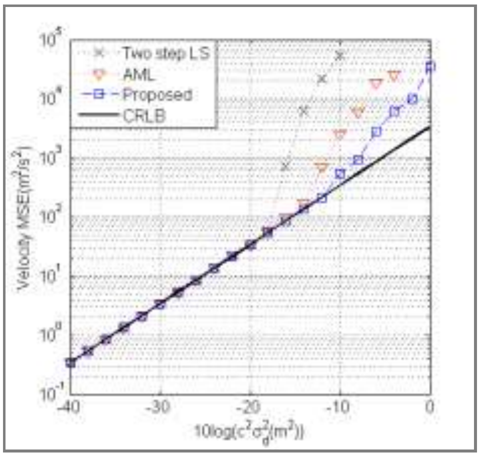
(b)

Figure 2: Comparison of (a) position and (b) velocity MSE of the proposed method, CRLB, and Two Step LS and AML for near field

The accuracy of position and velocity estimation (near filed source) of the proposed hybrid method in terms of MSE where, noise power increases from -20 dB to 20 dB is shown in Figure 2 (a), and (b). It is contrasted with the two-step WLS, AML and CRLB of TDOA and FDOA localization algorithms. The MSE of two-step WLS, proposed hybrid method and AML approximately reach CRLB below 6 dB noise level. The deviation of two-step WLS is started from CRLB at noise power 6 dB. Besides, the AML deviates from CRLB when the noise level is 12 dB, while the proposed method provides inaccurate estimates at the noise level 14 dB. Before threshold effect, the MSE's ratio of the proposed method in both cases (position and velocity) varies between 1.05 and 1.1 contrasted with CRLB. Therefore, the proposed method's threshold effect arises at a noise level that is approximately 2 dB and 8 dB later than that of AML and the two-step WLS as the noise level increases.



(a)



(b)

Figure 3: Comparison of (a) position and (b) velocity MSE of the proposed method, CRLB, and Two Step LS and AML for far field

Figure 3 demonstrations the MSE of position and velocity at far field using the proposed hybrid method, AML, two-step WLS and CRLB at noise ranging from -40 dB to 0 dB in WSN. Below threshold effect (-14 dB) of two-step WLS, the MSE of all algorithms as the reference are almost same, where maximum variation is 1.07 times higher compared with CRLB. After threshold, the MSE of the proposed hybrid method, two-step WLS and AML become higher with an increment in noise level. However, the rising slope of the proposed hybrid method (position and velocity estimation of distant source) is lower than the AML and two-step WLS that is clearly depicted in Figure 3.

In conclusion, it is apparent that, the MSE of position and velocity of the far field source is higher than the near field due to the comparative different geometrical shape between source and sensor network. In our simulation results, the proposed hybrid method yields better results than the two step WLS and AML. Also, the proposed method in close proximity with the CRLB from near to far field source with same and various velocities and different baseline of network at varying noise level.

5. Conclusion

The non-linear localization equations set and measurement noise, a pose the challenges to locate the position and velocity of the locomotive source in the 2-D scenario based on TDOA and FDOA measurements in WSN geometry. In addition, CRLB achievement at ranges, low to high noise level is the main challenges. Moreover, Two step LS [17] and AML [16] achieved the CRLB for low to moderate noise level. In localization algorithm, ML is a powerful tool. In addition, GA is one of the best methods for optimization method. We have proposed a hybrid method comprised of ML and GA to estimate the position and velocity of moving source under Gaussian noise. Hence, the proposed method in WSN has provided better results than that of existing method in the same simulation environment and has reached the CRLB from low to high noise level.

References

[1] Amundson I., Koutsoukos X, A survey on localization for mobile wireless sensor networks, *Mobile Entity Localization and Tracking in GPS-less Environnments*, pp. 235-254, 2009.

[2] Ingram S., D. Harmer, M. Quinlan, Ultrawideband indoor positioning systems and their use in emergencies, *IEEE in Position Location and Navigation Symposium, PLANS* 2004.

[3] Grimes, Gary J, Cellular terminal for providing public emergency call location information, *U.S. Patent* No. 5479482, 26 Dec. 1995.

[4] Cai C., Yang C., Zhu, Q., Liang, Y., Collision avoidance in multi-robot systems, 2007.

[5] Jones, W.D., Keeping cars from crashing, *IEEE Spectrum*, Vol. 38, No.9, pp. 40-45, 2001.

[6] Amouris K., Position-based broadcast TDMA scheduling for mobile ad-hoc networks (MANETs) with advantaged nodes, *IEEE Conference on Military Communications*, 2005.

[7] Sumathy V., Narayanasmy P., Baskaran K, Purusothaman T, GLS *with* secure routing in ad-hoc networks. *IEEE Conference on Convergent Technologies for Asia-Pacific Region*. 2003.

[8] Guvenc I., C. C. Chong, A survey on TOA based wireless localization and NLOS mitigation techniques. *IEEE Communications Surveys & Tutorials*, Vol. 11, No. 3, pp. 107-124, 2009.

[9] Wang G. H., Chen, An importance sampling method for TDOA-based source localization, *IEEE Transactions on Wireless Communications*, Vol. 10, No. 5, pp. 1560-1568, 2011.

[10] Bishop A. N., Fidan B, Doğançay K., Anderson B, Pathirana, P. N., Exploiting geometry for improved hybrid AOA/TDOA-based localization, *Signal Processinl*, Vol. 88, No.7, pp. 1775-1791, 2008.

[11] Meesookho C., Mitra U., Narayanan S., On energy-based acoustic source localization for sensor networks, *IEEE Transactions on Signal Processing*, Vol. 56, No. 1, pp. 365-377, 2008.

[12] Stefano G. D., Petricola A., A distributed AOA based localization *algorithm* for wireless sensor networks. *Journal of computers*, Vol. 3, No. 4, pp. 1-8, 2008.

[13] Wang, X., Z. Wang B. O'Dea, A TOA-based location algorithm reducing the errors due to non-line-of-sight (NLOS) propagation, *IEEE Transactions on Vehicular Technology*, vol. 52. No. 1, pp. 112-116, 2003.

[14] Ho K., Bias reduction for an explicit solution of source localization using TDOA, *IEEE Transactions on Signal Processing*, Vol. 60, No. 5, pp. 2101-2114, 2012.

[15] Chestnut P.C., Emitter location accuracy using TDOA and differential doppler. *IEEE Transactions on Aerospace and Electronic Systems* Vol. 2, pp. 214-218, 1982.

[16] Yu, H., Huang, G., Gao J., Wu X., Approximate Maximum Likelihood Algorithm for Moving Source Localization Using TDOA and FDOA Measurements. *Chinese Journal of Aeronautics*, Vol. 25, No. 4, pp. 593-597, 2012.

[17] Ho K., W. Xu, An accurate algebraic solution for moving source location using TDOA and FDOA measurements, *IEEE Transactions on Signal Processing*, Vol. 52, No. 9, pp. 2453-2463, 2004.

[18] Friedlander B., A passive localization algorithm and its accuracy analysis, *IEEE Journal of Oceanic Engineering, Vol*. 12, No. 1, pp. 234-245, 1987.

[19] Ho K., Y. Chan, Geolocation of a known altitude object from TDOA and FDOA measurements, *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 33, No. 3, pp. 770-783, 1997.

[20] Fowler, M.L., X. Hu, Signal models for TDOA/FDOA estimation, *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 44, No. 4, pp. 1543-1550, 2008.

[21] Takabayashi Y., Matsuzaki T., Kameda H., Ito M., Target tracking using TDOA/FDOA measurements in the distributed sensor network, *IEEE SICE Annual Conference*, 2008.

[22] Sheng X., Y.-H. Hu., Maximum likelihood multiple-source localization using acoustic energy measurements with wireless sensor networks, *IEEE Transactions on Signal Processing*, Vol. 53, No. 1, pp. 44-53, 2005.

[23] Davis L., *Handbook of genetic algorithms*, Van Nostrand Reinhold New York, Vol. 115, 1991.

[24] Houck C.R., J. Joines, M.G. Kay, *A genetic algorithm for function optimization: a Matlab implementation.* NCSU-IE TR, Vol. 95, No. 9, 1995..

[25] Shen G., R. Zetik, R.S. Thoma, Performance comparison of TOA and TDOA based location estimation algorithms in LOS environment. *5th IEEE Workshop on Navigation and Communication in Positioning, WPNC*, 2008.

[26] Shi H., J. Cao, A new hybrid algorithm on TDOA localization in wireless sensor network. *IEEE International Conference on Information and Automation (ICIA)*, 2011.

[27] Sengijpta, S. K., *Fundamentals of statistical signal processing: Estimation theory*. *Technometrics*, Vol. 37, No. 4, pp. 465-466, 1995.

[28] Pourhomayoun M., M. Fowler., Cramer-Rao lower bounds for estimation of phase in LBI based localization systems, *Conference Record of the Forty Sixth Asilomar Conference on Signals, Systems and Computers (ASILOMAR)*. 2012.

[29] Chan Y., K. Ho, A simple and efficient estimator for hyperbolic location. *IEEE Transactions on Signal Processing*, Vol. 42, No. 8, pp. 1905-1915, 1994.