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An Effective Algorithm for Instantaneous Position Estimation of Moving Source Based on TDOA-FDOA in WSN

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***Abstract*:** Recently, in order to improve civilian safety, to increase the military security and to mitigate the disaster effect Electromagnetic (EM) source localization has become a vital issue. The localization is embedded in traffic alert, battle-field surveillance, emergency call 911 (E911), resource allocation and disaster effect mitigation. The emitter location can be determined by bestowing its transmitted signal which is measured at an array of spatially detached receivers. To estimate the EM source location, some methods have been establishedwhich include Time of Arrival (TOA), Time Difference of Arrival (TDOA), Frequency Difference of arrival (FDOA), Angle of Arrival (AOA), Received Signal Strength (RSS) and Acoustic Energy of the transmitted emitter signal. Associating all localization techniques, TDOA and FDOA (hyperbolic) are the simplest and the most operative ones. The position and velocity from the intersection point of hyperbola created from TDOA and FDOA can be estimated by the sensors situated on an axis in two-dimensional scenario measuring TDOA (the time difference of arrival) and FDOA (frequency difference of arrival) of the emitting signal from a moving source. Nevertheless, because of the non-linear localization equations set and measurement noise in wireless sensor network (WSN), the hyperbolas may not be intersected at a single point. Thus, it is significant to estimate a source position minimizing its deviations from the actual position. a hybrid method with maximum likelihood (ML) and genetic algorithm (GA) in the arbitrary sensor array network (ASAN) are planned in this paper in order to determine the instantaneous position of the moving source through estimating the velocity and position according to hyperbolic technique (TDOA and FDOA). Initially in the position and velocity localization data, ML is applied. Moreover, to acquire the globally best solution of localization parameters from non-linear equation sets of ML solution, GA is implemented. The obtained results prooved that the proposed methods 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 paper, explicit solutions, that are not achievable through the established methods in all cases, are provided by the proposed methods.

***Keywords*:** localization, hyperbolic technique, maximum likelihood, genetic algorithm**.**

1. Introduction

Electromagnetic (EM) sources are important parts of civilian and military applications. However, sometimes technology, which is related to EM sources is misused. For leading a better life, localization awareness plays a pivotal role in the civilian and military application. 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 emitter location can be perceived by applying its transmitted signal that is measured at an array of spatially detached 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 used for localization of the emitter. The information about the distance between the receivers and sensors is directly provided by TOAs, TDOA, RSS and acoustic energy. The AOA and MDF contributed in getting the source bearing are related 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 and MDF techniques are used to measure the arrival angle of the signal from the emitter to sensors and the direction of magnetic field respectively. The signal strength of sensors is utilized by RSS technique. In line of sight (LOS) signal propagation TOA, TDOA, AOA and RSS are usually used for locating the emitter position of stationary source in signal parameter based localization 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, designing and implementing of special receivers for AOA in time synchronization system [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 the 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, the application of Doppler theory called frequency difference of arrival (FDOA) is utilized to calculate the velocity combined with TDOA [15]. Still now, some degree of limitation is faced to locate the position of the stationary and the position and the velocity of moving emitter which are: i) Inconsistency problem when more than two for 2-D or more than three for 3-D TDOA and FDOA measurement are available, ii) Non-linear relation between source and sensors position that create 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 power tools to solve localization estimation problem is ML technique. But, a 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 [17-19]. For overcoming these challenges including low to high noise level, we have proposed a hybrid algorithm combined with ML and GA based on hyperbolic technique to estimate the position and velocity of a moving source in ASAN. Here, GA is implemented to get the worldwide best localization parameters solution from non-linear equation groups of ML solution. In this paper we simulated a hybrid method to estimate the position and velocity of moving source at near to far filed with same and different velocity 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 the performance evaluation is explained. Then, the limitations and future perspectives are discussed. Finally, the conclusion is presented.

2. Proposed Method

The *N* receivers of WSN are assumed in a two dimension (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 $i=1,\ 2,\ 3,\dots,\ N$. 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 is considered as 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 is i^{th} and the reference is t_{i1}. The equation (2) is rearranged as $d_{i1}^0 + d_1^0 = d_i^0$ and then both sides are squared. Substituting d_1^0 and d_i^0 from equation (1), the TDOA equation set obtained is,

$$d_{i1}^{0\,2} + 2d_1^0 d_{i1}^0 = R_i^T R_i - R_1^T R_1 - 2(R_i - R_1)^T p\ . \tag{3}$$

The equation (3) is a non-linear set with unknown d_1^0 and *p*, that creates *N*-1 hyperbolic curves with focus $R_i=[x_i\ y_i]^t$ where $i=1,2,\ 3,\dots,\ N$. 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 calculating the position and velocity of moving source. Conversely, TDOA equations set may be inadequate to provide the needed localization accuracy of moving source as TDOA calculates only 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 parameters is derived by the time derivative of the equation (1) as follows:

$$v_i^0 = \frac{(v-u_i)^T(p-R_i)}{d_i^0} \tag{4}$$

The FDOA is measured by the time derivative of the equation (3) as follows:

$$2(v_{i1}^0 d_{i1}^0 + v_{i1}^0 d_1^0 + d_{i1}^0 v_1^0) = 2(u_i^T R_i - u_1^T R_1 - (u_i - u_1)^T p - (R_i - R_1)^T v) \tag{5}$$

In terms of equation (5), 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 path way from source to a sensor. The velocity of EM waves is constant because 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 source to 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 Gaussian distribution but with fine support region. However, the LOS noise by a zero mean Gaussian is simulated in simulations of this paper. Therefore, the path difference and path difference rate measurements of the position localization technique are modeled as follows:

$$d_{i1} = d_{i1}^0 + n_{i1} \tag{6}$$

$$v_{i1} = v_{i1}^0 + nv_{i1} \tag{7}$$

Here, n_{i1} and nv_{i1} are additive white Gaussian noise for LOS. In this paper, we have focused our research to calculate the position and velocity of emitter considering only LOS noise. Hence, The vector of noisy TDOA and FDOA, $D=[d_{21}\ d_{31}\dots d_{N1}]$ and $V=[v_{21}\ v_{31}\dots v_{N1}]$ have a covariance matrix [17, 21].

$$Q = E\{[D^T\ \ V^T]^T[D^T\ \ V^T]\} = \sigma^2\begin{bmatrix} Q_1 & O \\ 0 & Q_1 \end{bmatrix} \tag{8}$$

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.

Substituting the d_{i1} and v_{i1} in equations (3) and (5), the two non-linear equation sets obtained as

$$2(R_i - R_1)^T p + 2d_{i1}d_1^0 = -d_{i1}^2 + R_i^T R_i - R_1^T R_1 \qquad (9)$$

$$2(v_{i1}d_1^0 + d_{i1}v_1^0 + d_{i1}v_{i1}) = 2(u_i^T R_i - u_1^T R_1 - (u_i - u_1)^T p - (R_i - R_1)^T v) \qquad (10)$$

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

$$([D^T\ V^T]^T / \alpha) = (2\pi)^{-\frac{N}{2}} (\det(Q))^{-\frac{1}{2}} \exp\{-\frac{j_1}{2}\} \ . \qquad (11)$$

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

$$J_1(\alpha) = \sum_{i=2}^{N} ((d_{i1} - d_{i1}^0)^2 + (v_{i1} - v_{i1}^0)^2) \quad . \qquad (12)$$

We can obtain the auxiliary vector of the position and velocity of the moving source by utilizing the optimization process into equation (12). A GA is a search heuristic mimicing the natural evolution process . To generate useful solutions to optimization and to search problems this heuristic is regularly used. Genetic algorithms are related to the greater class of Evolutionary algorithms (EA) generating solutions to optimize problems through techniques enthused by natural evolution, for example inheritance, mutation, selection, and crossover [23, 24]. Henceforth, GA is regarded as one of the best methods to the global optimization that is clarified in the following [25, 26]. Thus, we have implemented the GA to realize the best approximation of auxiliary vector. A procedure of a simple GA has been specified as following:

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 ASAN was applied which permitted maximizing the value of J_1. For optimizing the non-linear equation sets of moving source localization in ASAN, 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 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.* For example, two binary strings of the Chromosomes include B1 and B2 in which,

B1= 1 0 1 1 0 1

B2= 0 1 1 0 1 0

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

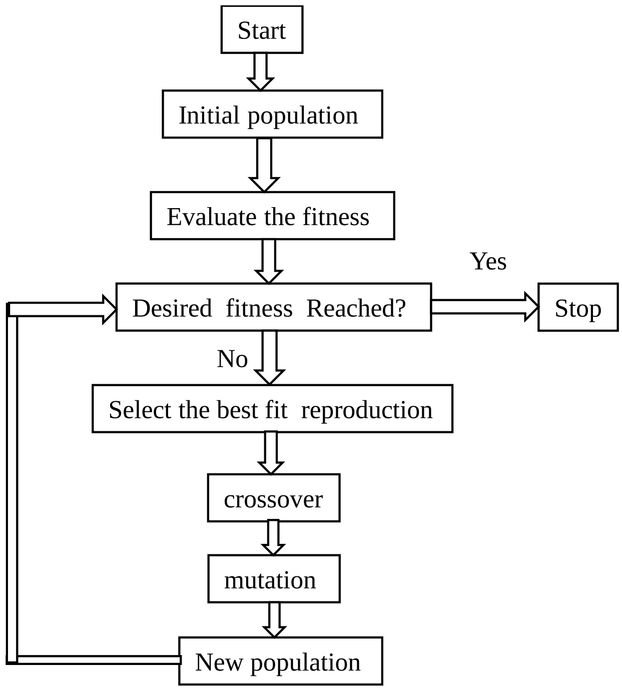


Figure 1. Block Diagram of simple GA

2.2. Crossover

After the determination operation for generating new results based on the current results in the sample, the genetic operator is applied. Two kinds of essential specialists can be seen, on one side there is a crossover and on the other is mutation. The crossover operation input is a couple of Chromosome named Guardians and the given output reproduced Chromosome called as Children. The Groups related to individuals were chosen arbitrarily from the mating pool based on the crossover probability. If the parallel letter set was applied within GA then every spot was given transformation probability from 0 to 1. Commonly there is low quality in variation.

In two steps, the crossover is completed for two designated Chromosomes. 1) The samples are signified by the binary strings 2) two Chromosomes do crossover in which binary strings can be switched based on the probability distribution. Consequently, for these Chromosomes single and two-point crossovers are applied. The crossover point is adopted using uniform probability distribution. For example, proided that 5 is the crossover site, the above-mentioned B1 and B2 is altered after the first step crossover and A1 and A2 will be

S1= 1 0 1 1 1 0
S2= 0 1 1 0 0 1

in the first step, the uniform crossover is used by the sample. To find out the common mark the common terms, in this step 2 the common terms are searched and binary strings are created in both parents,. In the string template, when there is matching term in both parents, the binary bit will be set to 1, if not it will be zero. Once more, two numbers are selected randomly and exchanged with each other from the population. For example, proided that 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 are made crossover with B1 and B2, after the first step crossover the two parents Chromosomes are changed. The new children will be:

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

To increase the diversity, the second step crossover is done and the new Chromosomes become

T1= 1 0 1 1 1 0 21 17 11 12 15 19 10 13 16
T2= 0 1 1 0 0 1 9 13 15 14 20 17 11

To reach the very least or perhaps greatest position for search engine optimization within GA, procedure as well as progress of selection are usually duplicated. The Genetic algorithm (GA) operation is finished when the fitness of the best Chromosome does not vary meaningfully.

2.3. Mutation

Mutation is defined as changing a small number of bases accidentally with small probability. which is performed to maintain the diversity in the population. This operation is essential to avoid the parameter convergence. The proper convergence of Genetic Algorithm depends upon its configuration that is a very important issue. This convergence is the result of defining the control parameters such as the population size, the Chromosome size, mutation rate and crossover point. Awkwardly, to determining these parameters is a very difficult task and normally they are defined empirically. In the population, each selected Chromosome was mutated separately, like the crossover. In the corresponding complimentary subset of the string, the operator changes with a randomly selected term. In this case a simple point mutation is applied. As an example, after mutation, T1 will be as follows: T1= 1 0 0 10 17 11 12 15 19 48 13 16

For the genetic algorithm configuration, parameters were:

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

3. Theoretical Lowed bound

Knowing the optimum achievable localization accuracy which can be obtained with the available measurement set is important. 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 ASAN is equal to the inverse the Fisher matrix that is defined as [17]

$$J = E[(\frac{\partial Inp(F;\beta)}{\partial\beta})^T(\frac{\partial Inp(F;\beta)}{\partial\beta})]_{\beta=\beta_0} \tag{13}$$

In terms of equation (13), $F=[d_{21}d_{31}d_{41}...d_{(N-1)1}, v_{21}v_{31}v_{41}...v_{(N-1)1}]^T$ is the vector of distance and distance rate differences based on TDOA and FDOA localization technique, where, $p(F;\beta)$ is the probability density function of *P*, where, β is the parameterized vector. 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 ASAN is obtained after taking log and performing differentiation as follows:

$$CRLB(\beta) = \{((\frac{\partial p^0(\beta)}{\partial\beta})^T Q^{-1}(\frac{\partial p^0(\beta)}{\partial\beta})_{\beta=\beta_0}\}^{-1} \tag{14}$$

The equation (14) can be represented as

$$\frac{\partial p^0(\beta)}{\partial\beta} = \begin{bmatrix} \frac{\partial D^0(\beta)}{\partial p} & \frac{\partial D^0(\beta)}{\partial v} \\ \frac{\partial V^0(\beta)}{\partial p} & \frac{\partial V^0(\beta)}{\partial v} \end{bmatrix} \tag{15}$$

where $D^0=[d^0_{21}\,d^0_{31}...\,d^0_{N1}]^T$, $V^0=[v^0_{21}\,v^0_{31}...\,v^0_{N1}]^T$, and $p^0(\theta)=[D^{0^T}\,V^{0^T}]^T$.

We obtained from equation (1)

$$d^0_{i1} = |p-R_i| - |p-R_1| \tag{16}$$

From equation (4), the equation (16) can be obtained.

$$v^0_{i1} = \frac{(v-u_i)^T(p-R_i)}{d^0_i} - \frac{(v-u_1)^T(p-R_1)}{d^0_1} \tag{17}$$

Applying the partial derivation of d^0_{i1} and v^0_{i1} with respect to *p* and *v* yields in equation (18) to (21)

$$\frac{\partial D^0}{\partial p} = \begin{bmatrix} \frac{(p-R_2)^T}{d^0_2} - \frac{(p-R_1)^T}{d^0_1} \\ . \\ . \\ \frac{(p-R_N)^T}{d^0_N} - \frac{(p-R_1)^T}{d^0_1} \end{bmatrix}_{(N-1)\times 3} \tag{18}$$

$$\frac{\partial D^0}{\partial v} = 0_{(N-1)\times 3} \tag{19}$$

$$\frac{\partial V^0}{\partial p}=-\begin{bmatrix}\frac{(p-R_2)^T v_2(\beta)}{d_2^{0^2}}-\frac{(p-R_1)^T v_1(\beta)}{d_1^{0^2}}-\frac{(v-u_2)^T}{d_2^0}+\frac{(v-u_1)^T}{d_1^0}\\ \cdot\\ \cdot\\ \frac{(p-R_N)^T v_N(\beta)}{d_N^{0^2}}-\frac{(p-R_1)^T v_1(\beta)}{d_1^{0^2}}-\frac{(v-u_N)^T}{d_N^0}+\frac{(v-u_1)^T}{d_1^0}\end{bmatrix} \quad (20)$$

$$\frac{\partial V^0}{\partial v}=0_{(N-1)\times 3} \quad (21)$$

Substituting the all necessary value from equation (18) to (21), into equation (14), 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 ASAN, where, Gaussian noise was considered as $dB=10\log(\sigma^2)$. The MSE of the proposed method 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. regaRding 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 fields where the velocity v^0 was (-2m/s, 1.5m/s) for all cases [29]. Besides, the moving sensors of position and velocity were shown in Table 1.

Table 1. Position and velocity coordinates of sensors in ASAN

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

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 algorithm. The MSE of two-step WLS, proposed hybrid method and AML approximately reach the theoretical performance (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 against 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.

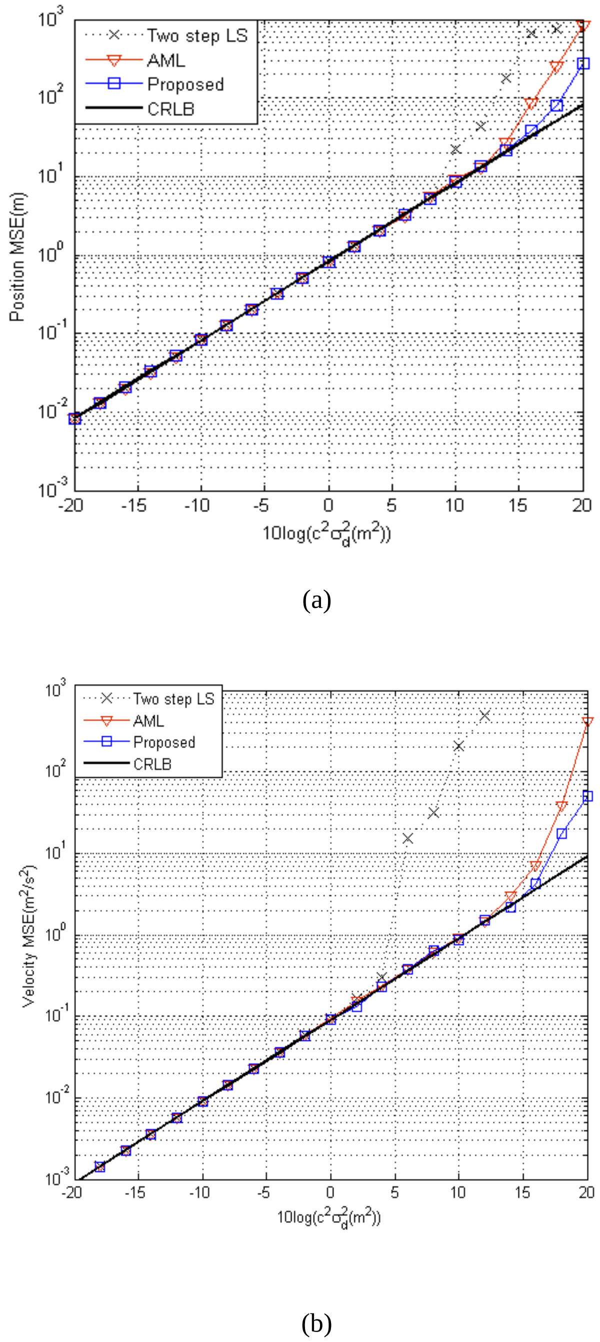
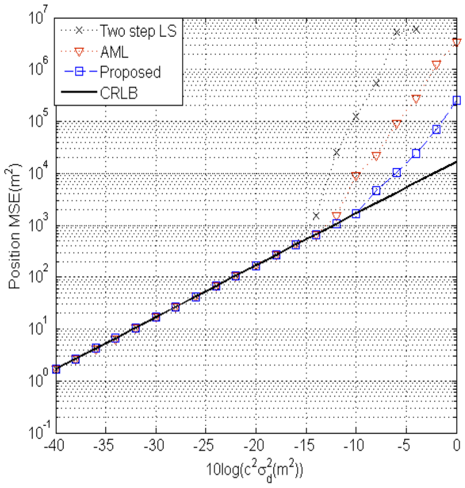
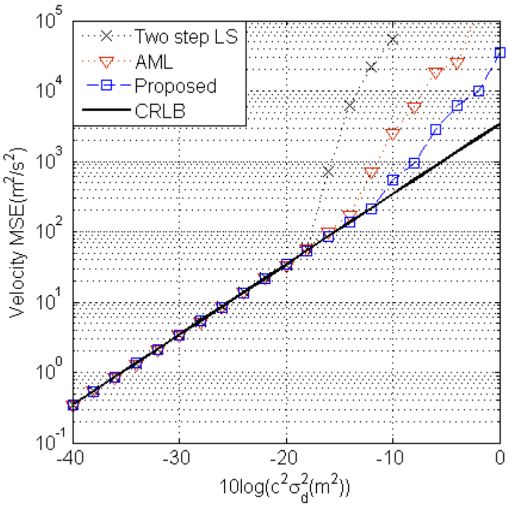


Figure 2. Comparison of (a) position and (b) velocity MSE of the proposed method, CRLB, and Two Step LS and AML for near field

Figure 3 demonstrates 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 ASAN. 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.



(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

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. 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 ASAN geometry. In addition, CRLB achievement at ranging 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 ASAN have provided the better results than that of existing method in same simulation environment and have reached the CRLB from low to high nose level.

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