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Optimization of Moving Vehicles Locating to Reduce Path Loss using the PSO Algorithm

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Abstract

Today, the use of case networks is widely used in various aspects, including on the road, because of their many applications. Road networks are used to create features such as road accident prevention, accident detection and on the other hand tracking and locating cars. The issue of locating cars is one of the core capabilities of mobile networks and uses time-domain methods such as TDOA for locating. These methods of locating are associated with errors in which the PSO optimization algorithm is used to reduce the locating error. This method generates nodes with less error by applying an optimization scenario and changing the TDOA coefficients.

Keywords: *Case Networks, The PSO Algorithm, Path Loss, Locating, TDOA Coefficient*

1. Introduction

Case networks are wireless and without infrastructure. On the other hand, these networks are classified as mobile networks. Understanding the characteristics of these networks are essential for examining these networks and studying the security risks and strategies for dealing with them. The following are some of the most important features of a case network:

Wireless: Communications are made in case networks using radio signals.

Without Infrastructure: This type of network is created by nodes in different cases as needed and has no infrastructure.

Importance of energy: Usually in such networks, each node has limited energy and does not have easy access to the energy source. So he tries to make the best use of his power.

Mobility: As mentioned, nodes may have displacement during communication.

Dynamic topology: This property result immediately from mobility. Because by moving a node, it may be disconnected from some of its neighbors or able to communicate with some new neighbors. In the case network, each node acts as a router itself and does not require an independent router [4].

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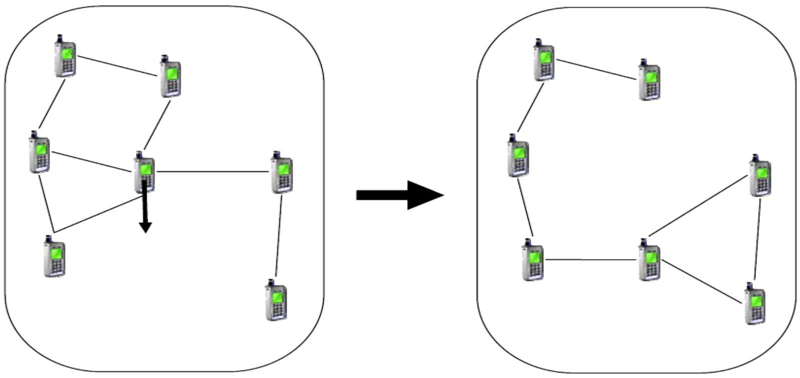

Figure 1. Modification of the case network topology due to node mobility [4].

Case wireless networks include a set of distributed nodes that communicate wirelessly with one another. Nodes can be host computers or routers. The nodes communicate directly with any access point and are not a stable organizations and are therefore formed into a custom topology. Each node is equipped with a transmitter and receiver. The most important feature of these networks is the existence of a dynamic and variable topology resulting from the mobility of the nodes. The nodes in these networks are constantly changing their location, which necessitates a routing protocol that is capable of adapting to these changes. Routing and security on this network are some of the challenges today.

Their case wireless networks are of two types:

• Intelligent sensor networks

• Case mobile networks

In the case of routing in case networks, the type of hardware sensor imposes restrictions on the network that must be considered in the choice of routing method [2]. Including that the power supply in the nodes is limited and in practice it is not possible to replace or recharge it; therefore, the proposed routing method of these networks should make the best use of the available energy, ie it must be aware of the node sources and if The node did not have enough resources to send the packet of its destination. Case topology may have unidirectional paths, whereas in fixed networks the paths are often bidirectional. This is an important issue in protocol design. In Figure 2, node A does not allow data or information to be sent directly to node D. However since all nodes are routers, A sends data packets of B. B sends it to C and finally, C sends it to D. Thus, although D does not directly have access to A, it reaches A through the middle nodes which are our routers [8].

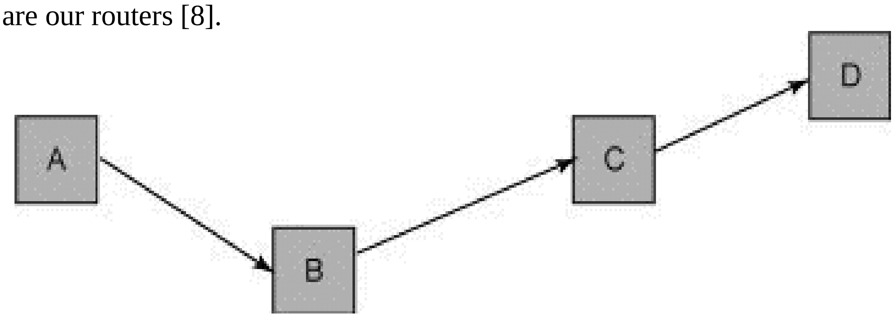

Figure 2. Nodes as complete routers [8].

The top grid are multi-hop. Bluetooth is an example of case networks that operate as a single hop [5].

1.1. Types of Case Networks

Mobile case networks are divided into two general categories: smart sensor networks and mobile case networks.

1.1.1. Intelligent Sensor Network (SSN)

It consists of several sensors located within a certain geographical area. Each sensor has wireless communication capability and sufficient intelligence for signal processing and networking capability.

1.1.2. Mobile Case Network (MANET)

It is a standalone set that communicates with each other via wireless links. The nodes in these networks are equipped with wireless receivers and transmitters and use antennas that may be broad or symmetrical. A mobile case network is a set of mobile or mobile nodes equipped with a receiver and transmitter for wireless communication. Mobile nodes cannot communicate directly with all nodes due to restrictions on their transceivers. For this reason, it is necessary to transmit data onto other nodes that play the role of a router in cases where such direct communication is not possible. However, the mobility of the nodes causes the network to be constantly changing and there are different paths of the two nodes. Other factors such as multiple hops, large network size, heterogeneity of host types and their variety and structure, and battery limitations have made designing proper routing protocols a serious problem. Appropriate and secure protocols should be used for this purpose. The nodes also have no prior knowledge of the network topology within their range. The common method is for a new node to announce itself and listen to extended bandwidth information on its neighbors in order to obtain information about the nodes around and how to access them[6].

2. Implementation Algorithm

A three-dimensional space with a moving target (K) is considered a vehicle. The position and velocity of each moving target K is considered p_i and v_i respectively. In this method, it is assumed that a source or a set of sensors receives the reflection signals from K of the moving target, which has a specified position and velocity P and V, respectively. The following equations are used to calculate the amplitude difference in signals obtained from the K moving target [1]:

$$x_{i1} = \left||P - p_i|\right| - \left||P - p_1|\right| + n_{i1} = d_i - d_1 + n_{i1} \;\; ; \quad i = 2. \dots . K \tag{1}$$

and

$$\dot{x}_{i1} = \frac{(V - \dot{p}_i)^T (P - p_i)}{||P - p_i||} - \frac{(V - \dot{p}_1)(P - p_1)}{\left||P - p_1|\right|} + \dot{n}_{i1} = \dot{d}_i - \dot{d}_1 + \dot{n}_{i1} \;\; ; \quad i = 2. \dots . K \tag{2}$$

Where

$$d_i = \left||P - p_i|\right| \; . \;\; \dot{d}_i = \frac{(V - \dot{p}_i)^T (P - p_i)}{\left||P - p_i|\right|} \qquad i = 1. \dots . K \tag{3}$$

In the above relationships, the noise amplitude difference and the noise amplitude difference rate are also considered based on the parameters n_i1 and n ̇_i1. Based on the TDOA and FDOA methods, the following method is used to measure time and frequency differences [7]:

$$t_{i1} = \frac{x_{i1}}{c} \quad . \quad f_{i1} = \frac{f_0 \dot{x}_{i1}}{c} \quad . \quad i = 2. \dots . K \tag{4}$$

Where c is the signal propagation rate and the carrier frequency f_0.

It is assumed that n_{i1} and $\dot{n}_{i1}$ are Gaussian random variables with a mean of zero and

$$n = [n_{21}. \dots . n_{K1}]^T Q = \mathbb{E}(nn^T) \cdot \dot{n} = [\dot{n}_{21}. \dots . \dot{n}_{K1}]^T ،$$

and

$$\dot{Q} = \mathbb{E}(\dot{n}\dot{n}^T).$$

On the other:

$$\begin{gathered} x = [x_{21}. \dots . x_{K1}]^T \ . \ \dot{x} = [\dot{x}_{21}. \dots . \dot{x}_{K1}]^T \\ d = [d_{21}. \dots . d_{K1}]^T \ . \ \dot{d} = \left[\dot{d}_{21}. \dots . \dot{d}_{K1}\right]^T \end{gathered} \tag{5}$$

Thus, the problem of estimating location and velocity, P and V, is expressed as follows:

$$min(x - Ad)^T(x - Ad) + \left(\dot{x} - A\dot{d}\right)^T \dot{Q}^{-1}(\dot{x} - A\dot{d}) \tag{6}$$

$$s.t. d_i = ||P - p_i|| \ . \ \dot{d}_i = \frac{(V - \dot{p}_i)^T(P - p_i)}{||P - p_i||} \qquad i = 1. \dots . K \tag{7}$$

Where:

$$A = [-\mathbf{1}_{M-1} \ \mathbf{1}_{M-1}] \tag{8}$$

3. The PSO Algorithm for Location Optimization

PSO algorithm is one of the desirable techniques for solving various problems such as numerical programming problems and numerical optimization problems. The basis of the PSO algorithm is based on particle velocity variations as algorithm inputs and optimization based on predefined targets. As mentioned, in the problem of locating TDOA and FDOA methods, estimating the locating error is a nonlinear equation. This process increases the error rate as well as the computation time and thus reduces the reliability of the location system. Therefore, the PSO algorithm is used [5]. Therefore, in the PSO algorithm two different problems are optimized. The first are the problem of calculating the location error and the second is the speed calculation error.

The problem of computing location based on PSO algorithm is as follows:

$$\begin{gathered} \min_{x} MSE \\ MSE < (x - Ad)^T(x - Ad) + \left(\dot{x} - A\dot{d}\right)^T \dot{Q}^{-1}\left(\dot{x} - A\dot{d}\right) = f^T x + (b - By)^T \dot{x}_i; \\ i = 1.\dots.K \\ (b - By)^T \dot{x}_l \leq 0 \;;\; l = 1.\dots.L \end{gathered} \tag{9}$$

So the parsed problems are transformed into the following relationships:

$$\begin{gathered} \max_{P} f^T \dot{x}_i + (b - B\dot{x}_l)^T x_i \\ A^T x_i \leq c \\ x_i \geq 0 \end{gathered} \tag{10}$$

And for the speed estimation error problem, the PSO algorithm has the following equations:

$$\begin{gathered} \max_{V} g^T \dot{v}_i + (n - N\dot{v}_l)^T v_i \\ M^T v_i \leq s \\ v_i \geq 0 \end{gathered} \tag{11}$$

In this way, the error of locating and estimating velocity using the PSO algorithm becomes linear and simpler equations. This approach will dramatically increase the accuracy and speed of calculations for locating moving targets. Finally, the PSO algorithm scenario of targeting is summarized as follows:

The PSO algorithm can be stated as:

{initialization}

$\dot{x}_i$:= initial feasible integer solution

$LB := -\infty$

$UB := +\infty$

While $UB - LB > \varepsilon$ do

{solve subproblem}

$\max_{P} f^T \dot{x}_i + (b - B\dot{x}_l)^T x_i | A^T x_i \leq c \,.\, x_i \geq 0$

if Unbounded then

Get unbounded ray P

Add cut $(b - B\dot{x}_l)^T x_i$ to master problem

else

Get extreme point P

Add cut $(b - By)^T \dot{x}_l \leq 0$ to master problem

$UB := \min(UB.\max_{P} f^T \dot{x}_i + (b - B\dot{x}_l)^T x_i)$

end if

{solve master problem}

$\min\{\mathrm{MSE}|\mathrm{cuts}.\dot{x}_i\}$

$\mathrm{LB} := \mathrm{MSE}$

end while

So the main problem become two linear sub-problems. In this way, the problem becomes simpler and as such, the location based on the PSO algorithm is summarized as follows: Consider the parameters $h = [d^T\ \dot{d}^T]$ and $A_1 = A[I_K\ 0_{K.K}]$ and $A_2 = A[0_{K.K}\ I_K]$. So the problem of location is defined as follows:

$$\begin{gathered} \min\{(x - A_1 h)^T Q^{-1}(x - A_1 h) + (\dot{x} - A_2 h)^T Q^{-1}(\dot{x} - A_2 h) + \cdots\} \\ s.t.\, h_i = ||P - p_i|| \\ h_{K+i} = \frac{(V - v_i)^T (P - p_i)}{||P - p_i||} \quad .\ i = 1. \dots. K \end{gathered} \tag{12}$$

Therefore, the simplification of the locating error estimation equation is summarized as Equation 13:

$$tr[A_1^T Q^{-1} A_1 + A_2^T \dot{Q}^{-1} A_2)H] - 2h^T\left(A_1^T \dot{Q}^{-1} x + A_2^T \dot{Q}^{-1} x + A_2^T \dot{Q}^{-1} \dot{x}\right) + \cdots] \tag{13}$$

Where $H = hh^T$ and $tr()$ represent the tracking matrix. The main problem in the above relationship are the linearity of H and h which is not the case initially. But using the PSO algorithm, these two parameters are linearized. But the next issue is the limitations of obtaining locating matrices. It is assumed that $X = [P\ \ V]$ and $Y = X^T X$. Therefore the constraint on $h_i = ||P - p_i||$ Considered as follows:

$$H_{i.i} = h_i^2 = Y(1.1) - 2X(:.1)^T p_i + p_i^T p_i \quad .\ i = 1. \dots. K \tag{14}$$

Thus

$$\begin{gathered} H_{i,j} \geq \left|Y(1.1) - X(:.1)^T (p_i + p_j) + p_i^T p_j\right| \ . \\ 1 \leq i < j \leq K \end{gathered} \tag{15}$$

On the other hand, the speed limit is also expressed as follows:

$$h_i h_{K+i} = (V - v_i)^T (P - p_i) \ .\ \ i = 1. \dots. K \tag{16}$$

Similarly, this constraint is applied to the location matrix by:

$$H_{i.K+i} = Y(2.1) - X(:.2)^2 p_i - X(:.1)^T v_i + p_i^T v_i \tag{17}$$

Finally, on the basis of the constraints presented, the two constraints $H = hh^T$ and $Y = X^T X$ remain. Using the PSO algorithm, these two constraints can be considered as $H \geq hh^T$ and $Y \geq X^T X$ equations. Therefore, this equation is applied to Equation 18 after being optimized by the PSO algorithm:

$$\begin{bmatrix} 1 & h^T \\ h & H \end{bmatrix} \geq 0 \ . \ \begin{bmatrix} I_3 & X \\ X^T & Y \end{bmatrix} \geq 0 \tag{18}$$

Finally, the positioning algorithm based on PSO algorithm and using TDOA and FDOA techniques is expressed as follows:

Require:

TDOA/FDOA measurements: $x_{i1}, \dot{x}_{i1}$;

Sensor positions and velocities: p_i, v_i;

Covariance matrix of TDOA/FDOA measurement noises:$Q. \dot{Q}$;

Number of iterations: L;

Ensure:

Target position and velocity estimates: $\hat{p}_n$ and $\hat{v}_n$;

1: Solving the target localization and the constraints, then using the estimates (P and V)

2: Solving the PSO Algorithm

3: Using $\hat{p}_0$ and $\hat{v}_0$ to update localization

4: for $n \leq L$;

5: Solving the problem, obtaining the new velocity estimate: $\hat{v'}_n$;

6: Solving the problem, obtaining the new position estimate: $\hat{p'}_n$;

7: Using $\hat{p}_n$ and $\hat{v}_n$ to update localization

8: End;

4. Simulation Results

Different numerical simulations have been considered to evaluate the performance of the proposed method. The proposed algorithm is compared with the SDP algorithm presented in [10] by Ding et al., As well as the 2SWLS algorithm in [9]. To evaluate the performance of the proposed method, the MSE parameter is used in relation to the relationship $MSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left|\left|x_j - x\right|\right|^2}$ The correct position or velocity and the x_j position or velocity are estimated. The noise in TDOA and FDOA measurements is considered as Gaussian random noise: $Q = \sigma^2\sum$ and $\dot{Q} = 0.1\sigma^2\sum$, where σ^2 represents the amplitude of the noise. On the other hand, Table 1 shows the position of the sensors in the network. The simulation results based on the positioning of the sensors are presented in Table 1.

Tabale. 1. Positioning of Sensors in the Network

Sensor no.	x	y	z	$\dot{x}$	$\dot{y}$	$\dot{z}$
1	*300*	*100*	*150*	*30*	*-20*	*20*
2	*400*	*150*	*100*	*-30*	*10*	*20*
3	*300*	*500*	*200*	*10*	*-20*	*10*
4	*350*	*200*	*100*	*10*	*20*	*30*
5	*-100*	*-100*	*-100*	*-20*	*10*	*10*

In Figures 3 to 8, the performance of MSE and BIAS for position and velocity estimation is presented and compared with the methods considered. Also in Figures 9 and 10, estimation of position estimation time and velocity is compared with SDP and 2SWLS methods.

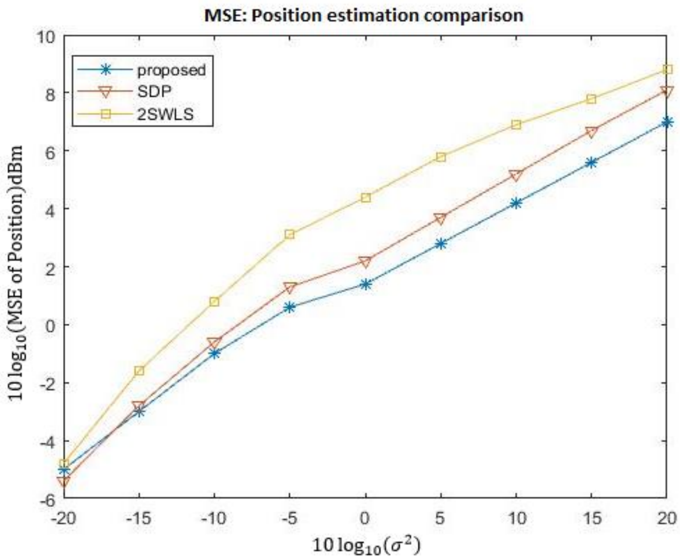

Figure 3. Comparison of MSE for position estimation.

As can be seen in Figure 3, the MSE is in a more favorable condition based on the position and velocity of the sensors for the proposed algorithm than the other two algorithms. The reason for this is that the PSO algorithm is a multi-objective optimization algorithm that can achieve the desired result.

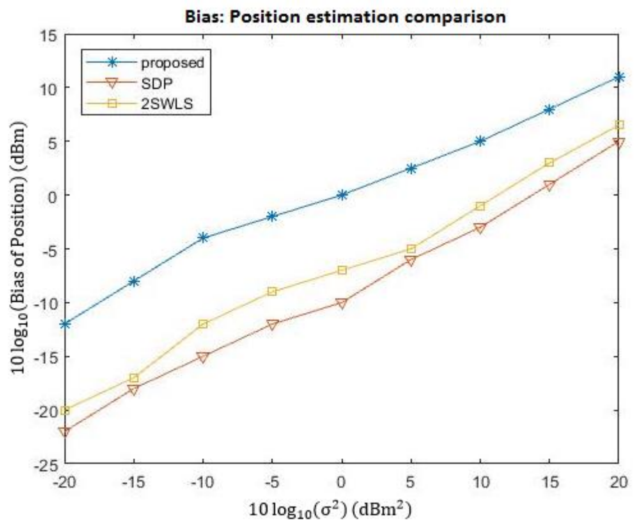

Figure 4. Comparison of Bias for position estimation.

As can be seen in Figure 4, the proposed method has a higher bias value. Bypass means the degree of concordance between the results of all data onto network nodes. In other words, for the network that we want to obtain the location for all of its moving nodes, the proposed method is higher.

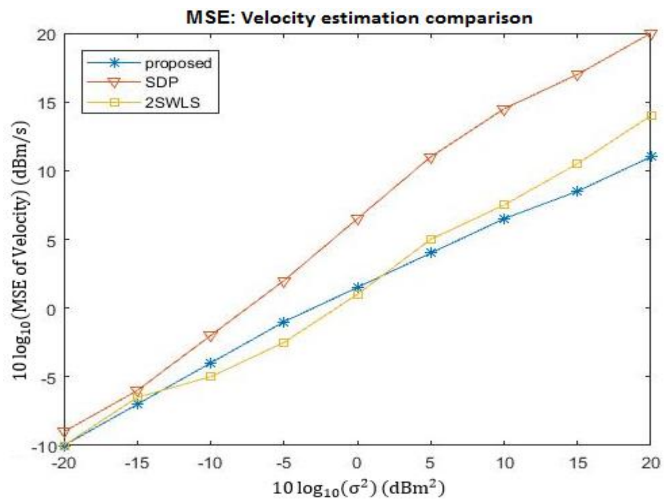

Figure 5. MSE Comparison for Speed Estimation.

Figure 5 shows another case of the proposed method based on different positions and velocity for the sensors and again the proposed algorithm has lower MSE.

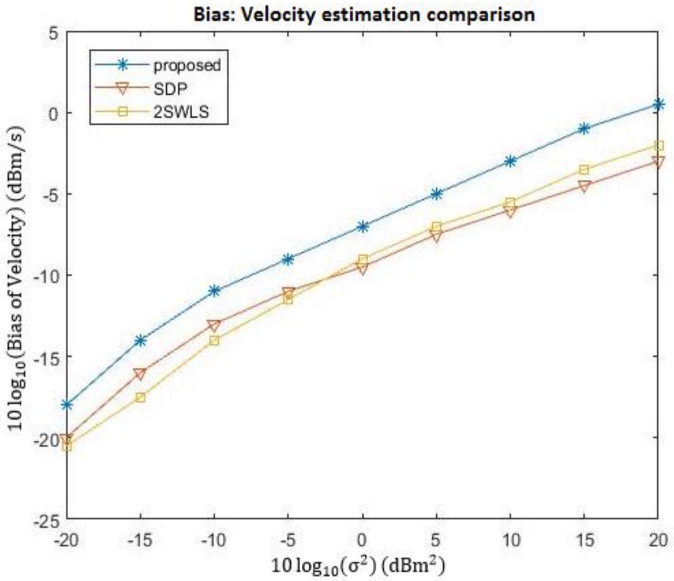

Figure 6. Bias Comparison for Speed Estimation.

The bias-related results in the case presented in Figure 6 is shown to show a higher bias rate than the proposed method.

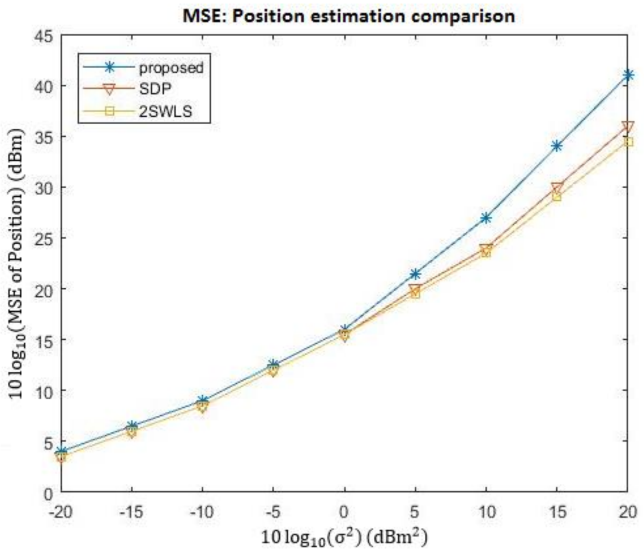

Figure 7. Comparison of MSE for position estimation.

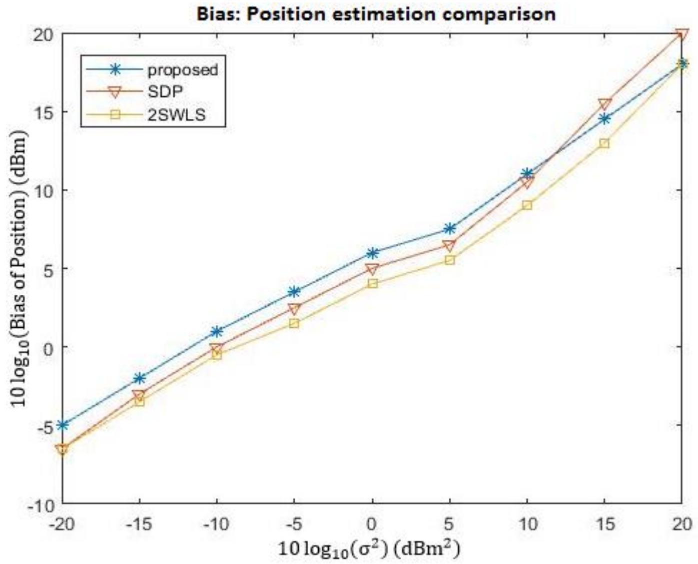

Figure 8. Comparison of Bias for position estimation.

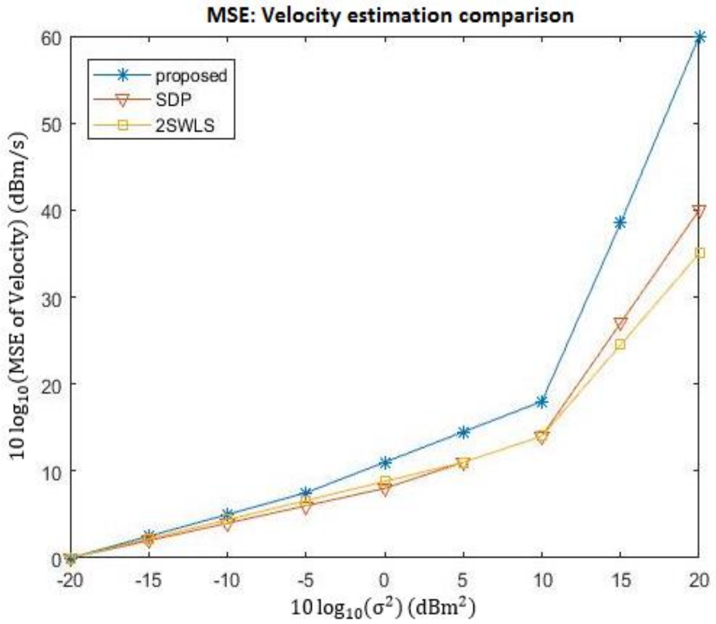

Figure 9. Comparison of MSE for velocity estimation.

Figure 9 shows the MSE parameters for speed estimation. The proposed method of estimating velocity has not been able to perform better than the other two methods.

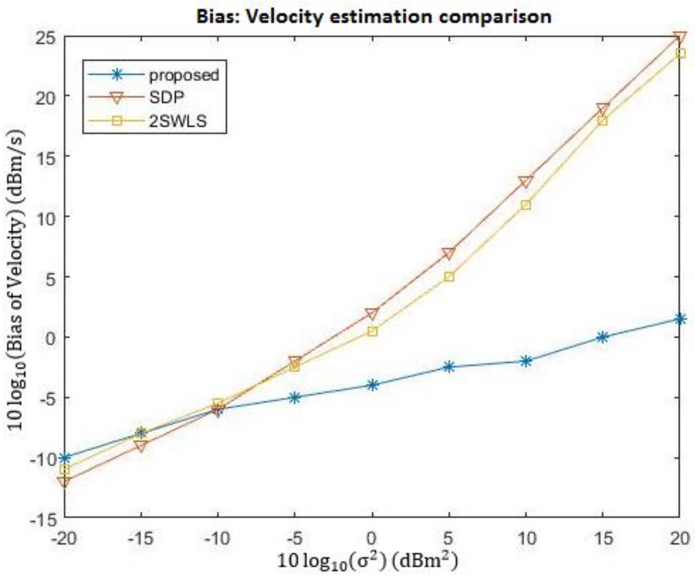

Figure 10. Bias Comparison for Speed Estimation.

On the other hand, the bias for the speed estimation in the proposed method is lower than the other two methods, and therefore this method of estimating the speed cannot perform better than the location estimation.

5. Conclusion

The problem of locating and estimating the speed of moving targets is one of the most important and commonly used problems. Different approaches have been proposed to this regard as stated. The key is to estimate position and velocity in multiple moving targets. This is a complex problem and the error of estimating the position and velocity, which is derived from the MSE relationship, is a nonlinear problem. The simplest solution to this problem is to use one of the TDOA or FDOA methods of, which is of low accuracy for estimating position and velocity. In this paper, the PSO algorithm was used. The algorithm optimally solves the nonlinear MSE equation for optimizing the position and velocity estimation. It was shown that this method can perform positioning at a higher speed. On the other hand, its MSE rates are lower than SDP and 2SWLS algorithms. The main feature of this method are that it can accurately locate multiple targets.

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