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Performance Evaluation of Target Trajectory and Angular Position Discovery Methods in Wireless Sensor Networks

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PERFORMANCEEVALUATIONOFTARGETTRAJECTORYANDANGULARPOSITIONDISCOVERYMETHODSINWIRELESSSENSORNETWORKS

Strictly as per the compliance and regulations of:

Performance Evaluation of Target Trajectory and Angular Position Discovery Methods in Wireless Sensor Networks

Rashmi Ranjan Sahu [α] & Dr. Jitendranath Mungara [σ]

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I. Introduction

Wireless Sensor Networks (WSNs) consist of many no of small nodes .It can be an effective for collecting data from various environments. Each sensor sends its data to Base Station (BS) [4], and finally BS sends these data to end user. Clustering is considered as an effective approach to provide better data gathering and scalability for large sensor networks.

Sensor networks are the combination of distributed sensing, communication and computing. They lend themselves to various applications such as Military applications, environmental monitoring, and support for logistics, human-centric applications and robotics applications.

Since a large number of sensor nodes are closely deployed, neighbor nodes may be having very short distance among them. Hence, multi-hop communication [2] in wireless sensor networks consumes less power than the single hop communication which is a traditional approach. However, the multi-hop routing of WSNs often has to perform target detection not only with respect to the distance between the transmitting base station but also spatial separation with respect to each sensor is also required in order to accurately estimate the target in a sensor field.

II. Literature Survey

A wireless sensor network is an autonomous system of numerous tiny sensor nodes equipped with integrated sensing and data processing capabilities. These sensor networks are distinguished from other wireless networks by the fundamental constraints under which they operate, i.e., sensors have limited and un-replenish able power resources making energy management a critical issue in wireless sensor networks. So these sensors must utilize their energy as efficiently as possible.

Many no of sensors are randomly placed and the target does not follow a single uniform path. So the main challenge is to track the moving target .So it requires an efficient navigation control method. Enyang and Soura [1] studied a set of different algorithm for node deployment like TOA algorithm. Generally a target is signal emitter whose transmission is received by a number of sensors that is placed distributedly. Distributed inference methods [8] developed for graphical models comprise a principled approach for data fusion in sensor networks. The application of these methods, are distributed nature of computation and deployment coupled with communications bandwidth and energy constraints typical of many sensor networks. Traditional measures [1] of distortion are not sufficient to characterize the quality of approximation as they do not address in an explicit manner the resulting impact on inference .While both graphical models and a distributed sensor network [8] have network structures associated with them.

III. New Contributions

We are interested in target tracking by considering both moving targets and mobile sensors. The spatial resolution refers to how accurate a target's position can be measured by sensors, and the actual paths in wireless sensor networks. Here we used Time To Live (TTL) for route discovery and also we considered Min Hop for finding the path .We define the spatial resolution as the deviation between the estimated and the actual target trajectory path, which

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can be explained as the distance that a target is not covered by any mobile sensors. It includes a more general TOA [8] measurement model that accounts for the measurement noise due to multipath propagation and sensing error.

IV. Problem Statement

The problem of tracking signal-emitting mobile targets using navigated mobile sensors based on signal reception. The Mobile Sensor Collection node will initiate communication with other sensor nodes in the network and finds multiple measurements with respect to the target location and then the time of arrival of each signal from the sensor nodes is computed with respect to target by the mobile sensor collector node. The path which has the lowest TOA is said to be trajectory of the mobile node in the network. But this project not only computes the TOA [8] but only measures the spatial separation with respect to degrees so that the TDD [5] of the mobile target is also captured. The node deployment algorithm, which is responsible for deploying the nodes in a sensor area consider TTL and mean hop. It also checks which nodes are within the coverage range and which are not. The target is tracked by angular position discovery algorithm.

V. Mathematical Modeling

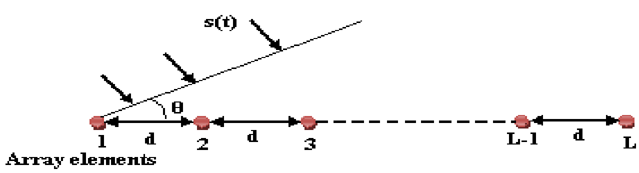

Figure 1 : Uniform Linear Array

Consider a uniform linear array geometry with L elements numbered 0, 1,…, L- 1 with a spacing of have half wavelength spacing ( ) between them. Let be the baseband signal that is received by each array element, but at a different time instant. If the phase of baseband signal received at element 0 is zero. By examining the geometry from figure 1, using basic trigonometry and facts from wave propagation, the time delay of arrival can be computed as

$$\Delta t_k = \frac{k\,D \sin\theta}{c} \qquad (1)$$

Where, is the speed of light, is an integer and is the direction from which plane wave is impinging on Sensor array

Suppose is a narrowband digitally modulated signal with low pass equivalent, carrier frequency , and symbol period . Narrow band signal can be written as

$$b(t) = \mathrm{Re}\left\{ b_l(t)\, e^{j2\pi f_c t} \right\} \qquad (2)$$

The signal received by the k[th] element is given by

$$x_k(t) = \mathrm{Re}\big(b_l(t-\Delta t_k)\big) e^{j2\pi f_c (t-\Delta t_k)} \qquad (3)$$

Now suppose that the received signal at the k[th] element is down converted to the baseband. In that case, the baseband received signal is defined as

$$x_k(t) = b_l(t-\Delta t_k)\, e^{-j2\pi f_c \Delta t_k} \qquad (4)$$

VI. Methodology

1. Node Deployment

This is responsible for placing the nodes in a given area

2. Coverage Area Determination

This module is used to determine the nodes which are reachable or to which a given sensor node can communicate directly

3. Picking the Next Sensor

The next sensor is picked randomly and target location is determined with respect to given sensor area.

4. Measuring the TOA

The TOA is measured with respect to the distance of the node and time of arrival of the detection packets.

5. Measuring the TDD

The Target Direction Detection of the signals with respect to the target is measured using MEV and CRLB approach

VII. Tracking Algorithms

a) Node deployment algorithm

Algorithm I

1.Input no of nodes ,node id,I,xmin,xmax,ymin,ymax.
2.if I<=no of nodes
3.Then x-coordinate position between Xmin to Xmax
4.Then y-coordinate position between Ymin to Ymax
5.Generate Node Id
6.Then I=I+1
7.End

The Node Deployment algorithm is used to randomly disperse the nodes across the network. It will place the node randomly in a network.

b) Path Discovery Algorithm

Algorithm 2(Path Discovery)

1. Input Source Node and Target Node
2. Fetch Routing Table
3. Fetch Neighbors
4. If neighbors contain Target
5. Route Discovered
6. Else Pick neighbor randomly
7. Then TTL=TTL-1

8. If TTL !=0
9. Then Go to Step 1
10. Else Min-Hop

The Individual Route Discovery Module is implemented by Time of Arrival 2 algorithm. . When a source node wants to send data to the sink, it includes a TTL of initial value N. It then randomly selects a neighbor for each share, and uni-casts the share to that neighbor. After getting the share, the neighbor first decrements the TTL. If the new TTL is greater than 0, then compares the neighbor list obtained from routing table with the list of nodes present in Node in Route (NIR Field). After getting the set of nodes not present in NIR. The neighbor is randomly picked from the neighboring nodes .When the TTL becomes 0, the last node receiving that share stops the random propagation of this share, and starts mooving it toward the sink using normal min-hop routing. The Min-Hop Routing algorithm picks the farthest node of its transmission range.

The minimum Hop Routing Algorithm used in the algorithm when TTL becomes zero works as below Min Hop routing algorithm picks the neighbor which is closest to the destination node. i.e. farthest node which is reachable.

c) Target Direction Detection Algorithm

Target Direction Detection of a mobile node with respect to spatial separation using different Filters approach are as follow.

We can get from (4)

The received baseband signal after sampling with a sampling period of T seconds is given by

$$x_k(nT) = b_l(nT - \Delta t_K)\, e^{-j2\pi f_c \Delta t_K} \qquad (5)$$

In a wireless digital communication system, the symbol period will be much greater than each of the propagation delays across the array given by

$$T \succ\succ \Delta t_K,\ k = 0,1,......., L-1 \qquad (6)$$

This allows the following approximation to be made

$$x_k(nT) \approx b_l(nT)\, e^{-j2\pi f_c \Delta t_K} \qquad (7)$$

The constants c and f_c can be related through the basic equation

$$c = f_c\, \lambda \qquad (8)$$

Where, λ is the wavelength of the propagating wave and f_c is the carrier frequency. The element spacing can be computed in wavelengths by using

$$d = \frac{D}{\lambda} \qquad (9)$$

Using the equations (1) and (8) in equation (7) we can arrive at equation

$$x_k(nT) \approx b_l(nT)\, e^{-j2\pi f_c \Delta t_K} = b_l(nT)\, e^{-j2\pi \frac{c}{\lambda} \frac{kD\sin(\theta)}{c}} \qquad (10)$$

Substituting the value of 'D' from equation (9) in equation (10) gives

$$x_k(nT) \approx b_l(nT)\, e^{-j2\pi \frac{c}{\lambda} \frac{k\,d\,\lambda \sin(\theta)}{c}} \qquad (11)$$

After simplifying, we get

$$x_k(nT) \approx b_l(nT)\, e^{-j2\pi\ k\,d\sin(\theta)} \qquad (12)$$

When discrete time notation is used with time index n, equation (12) can be written as

$$x_k(n) \approx b(n)\, e^{-j2\pi\ k\,d\sin(\theta)} \approx b(n)\, a_K(\theta) \qquad (13)$$

Where, $a_K(\theta) = e^{-j2\pi\ k\,d\sin(\theta)}$ and k is an integer in the range $0 \le k \le L-1$

Let the nth sample of the baseband signal at the kth element be denoted as $x_k(n)$ .When there are M signals present, the nth symbol of the ith signal will be denoted by $b_i(n)$ for $i = 0,1,2,...., M-1$. The baseband sampled signal at the kth element can be expressed as

$$x_k(n) \approx \sum_{i=0}^{M-1} b_i(n)\, a(\theta_i) \qquad (14)$$

i. *Formulation of Array Data Matrix*

By considering all the array elements, i.e $k = 0,1,2,....L-1$, equation (2.14) can be written in a matrix form as

$$\begin{bmatrix} x_0[n] \\ x_1[n] \\ . \\ . \\ . \\ x_{L-1} \end{bmatrix} = \begin{bmatrix} a_0(\theta_0) & a_0(\theta_1) \ldots\ldots\ldots\ldots & a_0(\theta_{M-1}) \\ a_1(\theta_0) & a_1(\theta_1) \ldots\ldots\ldots\ldots & a_1(\theta_{M-1}) \\ . & . & . \\ . & . & . \\ . & . & . \\ a_{M-1}(\theta_0) & a_{M-1}(\theta_1) \ldots\ldots & a_{M-1}(\theta_{M-1}) \end{bmatrix} \begin{bmatrix} b_0[n] \\ b_1[n] \\ . \\ . \\ . \\ b_{M-1}[n] \end{bmatrix} + \begin{bmatrix} n_0[n] \\ n_1[n] \\ . \\ . \\ . \\ n_{L-1} \end{bmatrix} \qquad (15)$$

Where , $n_k[n]$ is additive white Gaussian noise considered at each element, $x_K[n]$ is the induced signal, b_n is the amplitude of n[th] source, M is the number of sources, L is the number of Sensor elements and n_n is the amplitude of n[th] noise sample. Equation (2.15) can be written in compact form as

$$x_n = [a(\theta_0)\ a(\theta_1).......a(\theta_{L-1})]b_n + n_n = Ab_n + n_n \quad (16)$$

Where, $a(\theta_i) = [a_0(\theta_i)\ a_1(\theta_i).........a_{L-1}(\theta_i)]$ is called the steering vector for the angle θ_i .These form a linearly independent set assuming the Target Direction Detection of each of the M signals is different. The vector n_n represents the uncorrelated noise present at each Sensor element. Because the steering vectors are a function of the angles of arrival of the signals, the angles can be computed if the steering vectors are known or if a basis for the subspace spanned by these vectors A is known. The set of all possible steering vectors is known as the array manifold given by

$$A = \begin{bmatrix} a_0(\theta_0) & a_0(\theta_1) & ....a_0(\theta_{M-1}) \\ a_1(\theta_0) & a_1(\theta_1) & ....a_1(\theta_{M-1}) \\ . & . & . \\ . & . & . \\ . & . & . \\ a_{M-1}(\theta_0) & a_{M-1}(\theta_1) & ....a_{M-1}(\theta_{M-1}) \end{bmatrix} \quad (17)$$

ii. *Formation of Array Correlation Matrix or Spatial Covariance Matrix*

The spatial covariance matrix of the Sensor array can be computed as follows. Assume that b_n (signal) and n_n (noise) are uncorrelated, n_n is a vector of Gaussian white noise samples with zero mean. The spatial covariance matrix R is given by

$$R = E[x_n\ x_n^H] \quad (18)$$

Substituting x_n from equation (16) in equation (18), we can obtain

$$R_{xx} = E[(Ab_n + n_n)(Ab_n + n_n)^H] \quad (19)$$

Applying expectation operator (E) to signal b_n and noise n_n in equation (19) results in

$$R = AE[b_n\ b_n^H]A^H + E[n_n n_n^H] \quad (20)$$

Defining $R_{ss} = E[b_n\ b_n^H]$ and $E[n_n n_n^H] = \sigma^2 I$ one can obtain array correlation matrix given by

$$R = A\ R_{ss}\ A^H + \sigma^2 I \quad (21)$$

Where, R is LxL Array Correlation Matrix or Spatial Correlation matrix, A is LxM Array Manifold Vector, A^H is hermitian transpose of A, σ^2 is noise variance, I is LxL identity matrix and R_{ss} is MxM source amplitude matrix given by

$$R_{ss} = E[b_n\ b_n^H] = \begin{bmatrix} b_1 \\ b_2 \\ . \\ . \\ b_M \end{bmatrix} * [b_1^*\quad b_2^* ....b_M^*] = \quad (22)$$

$$\begin{bmatrix} b_1 b_1^* & 0 & \cdots & \cdots & 0 \\ 0 & b_2 b_2^* & \cdots & \cdots & 0 \\ \vdots & \vdots & \vdots & & \vdots \\ \vdots & \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & \cdots & b_M b_M^* \end{bmatrix}$$

Where $b_1, b_2, ...b_M$ are amplitudes of M signals (sources).

iii. *Finding Eigen value and Eigen Vectors of Array Correlation Matrix*

Eigen values and eigenvectors [4] provide useful and important information about a matrix. It is possible to determine whether a matrix is positive definite, invertible, indicate how sensitive determination of inverse will be to numerical errors. Eigen values and eigenvectors are useful in spectrum estimation and adaptive filtering problems.

The Eigen values of LxL Array Correlation matrix R is found by solving the characteristic equation given by

$$|R - \lambda I| = 0 \quad (23)$$

The solution to equation (23) gives L Eigen values $\{\lambda_1, \lambda_2, ..., \lambda_L\}$.

The Eigen Vector for specific Eigen value λ_a is found by solving the equation given by

$$R\ V_n = \lambda_a V_n \quad (24)$$

Where V_n is Lx1 matrix comprising of unknown variables. Expanding equation (24) in matrix notation,

$$\begin{bmatrix} R_{0,0} & R_{0,1} & \cdots & R_{0,L} \\ R_{1,0} & R_{1,1} & \cdots & R_{1,L} \\ \vdots & \vdots & \vdots & \vdots \\ R_{L,0} & R_{L,1} & \cdots & R_{L,L} \end{bmatrix} \begin{bmatrix} V_1 \\ V_2 \\ \vdots \\ V_L \end{bmatrix} = \lambda_a \begin{bmatrix} V_1 \\ V_2 \\ \vdots \\ V_L \end{bmatrix} \quad (25)$$

Multiplying the matrices, a set of simultaneous equations as defined in (26) are obtained

$$\begin{array}{l} R_{0,0}V_1 + R_{0,1}V_2 + \ldots\ldots\ldots\ldots + R_{0,L}V_L = \lambda_a V_1 \\ R_{1,0}V_1 + R_{1,1}V_2 + \ldots\ldots\ldots\ldots + R_{1,L}V_L = \lambda_a V_2 \\ \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots\;\vdots \\ R_{L,0}V_1 + R_{L,1}V_2 + \ldots\ldots\ldots\ldots + R_{L,L}V_L = \lambda_a V_L \end{array} \quad (26)$$

Since there are L Unknowns we have L simultaneous equations which can be solved to obtain $V_1, V_2, \ldots\ldots, V_L$. These L values form Eigen vector matrix.

a. *Kalman Filter*

This method finds a power spectrum such that its Fourier transform equals the measured correlation subjected to the constraint that its entropy is maximized. For estimating TDD from the measurements using an array of sensors, the Kalman method finds a continuous function $P_{MEv}(\theta) > 0$ such that it maximizes the entropy function.

The Kalman power spectrum is given by

$$P_{KALMAN} = \frac{1}{a^H(\theta) E_S E_s{}^H a(\theta)} \quad (27)$$

Where,

E_s = Maximum eigen vectors

$a^H(\theta) =$ Hermitian transpose of steering vector

b. *MMA Filter*

The Maximum Margin Analyzer is known as a MMA. It is also alternatively a maximum likelihood estimate of the power arriving from one direction while all other sources are considered as interference. Thus the goal is to maximize the Signal to Interference Ratio (SIR) while passing the signal of interest undistorted in phase and amplitude. The source correlation matrix R_{ss} is assumed to be diagonal. This maximized SIR is accomplished with a set of array weights given by

$$w_{mma} = \frac{R_{xx}^{-1} a(\theta)}{a^H(\theta) R_{xx}^{-1} a(\theta)} \quad (28)$$

Where, R_{xx}^{-1} is the inverse of un-weighted array correlation matrix R_{xx} and $a(\theta)$ is the steering vector for an angle θ. The MMA pseudo spectrum is given by

$$P_{MMA} = \frac{1}{a^H(\theta) R_{inv}\, a(\theta)} \quad (29)$$

Where, $a^H(\theta)$ is the hermitian transpose of $a(\theta)$ and R_{inv} is the inverse of autocorrelation matrix.

c. *WMMA Filter*

In this method [10] a rectangular window of uniform weighting is applied to the time series data to be analyzed. For bearing estimation problems using an array, this is equivalent to applying equal weighting on each element. WMMA Filter method is also called Ordinary Beam forming Method (OBM). This method estimates the mean power $P_B(\theta)$ by steering the array in θ direction.

The power spectrum in WMMA Filter method is given by

$$P_{WMA}(\theta) = \frac{S_\theta^H R S_\theta}{L^2} \quad (30)$$

Where, 'S_θ' denotes the steering vector associated θ,

'R' is the array correlation matrix.

'L' is the number of elements in the array

In DOA estimation, a set of steering vectors $\{S\theta\}$ associated with various direction θ is often referred to as the array manifold. From the array manifold ,the array correlation matrix, $PB(\theta)$ is computed. Peaks in $P_B(\theta)$ are then taken as the directions of the radiating sources.

d. *CRLB Filter*

CRLB is an acronym which stands for Carmer Roa Bound. CRLB provide correct estimates of the number of signals, angles of arrival and the strengths of the signal. CRLB makes the assumption that the noise in each channel is uncorrelated making the noise correlation matrix diagonal. However, under high Signal correlation the traditional CRLB algorithm breaks down and other methods must be implemented to correct this weakness.

The Eigen values and eigenvectors for correlation matrix R is found. M eigenvectors associated with the signals and $L-M$ eigenvectors associated with the noise are separated. For uncorrelated signals, the smallest Eigen values are equal to the variance of the noise. The $L\times(L-M)$ dimensional subspace spanned by the noise eigenvectors is given by

$$E_N = [e_1\, e_2\, e_3 \ldots\ldots\ldots\ldots\ldots\ldots\; e_{L-M}] \quad (31)$$

Where, e_i is the i[th] Eigen Value.

The noise subspace Eigen vectors [4] are orthogonal to the array steering vectors at the angles of arrival $\theta_1, \theta_2, \ldots\ldots\ldots\theta_M$. Because of this orthogonality condition, the Euclidean distance $d^2 = a(\theta)^H E_N E_N^H a(\theta) = 0$ for each and every angle of arrival $\theta_1, \theta_2, \ldots\ldots\ldots\theta_M$ .Placing this distance

$d^2 = a(\theta)^H E_N E_N^H a(\theta) = 0$ for each and every angle of arrival $\theta_1, \theta_2, ...\theta_M$ .Placing this distance expression in the denominator creates sharp peaks at the angles of arrival. The CRLB pseudo spectrum is given by

$$P_{CRLB} = \frac{1}{a(\theta)^H E_N E_N^H a(\theta)} \qquad (32)$$

Where, $a(\theta)$ is steering vector for an angle θ and E_N is L x L-M matrix comprising of noise Eigen vectors.

VIII. Simulation

In this section we will provide the examples to explain different result .After that we will compare between TOA1 and TOA2, CRLB with other three algorithms.

Algorithm	Number of Nodes	Source Node	Target Node	Coverage Area	TTL
TOA1	30	8	23	15	-
TOA2	30	8	23	15	2

a) Route Discovery using TOA1 Algorithm

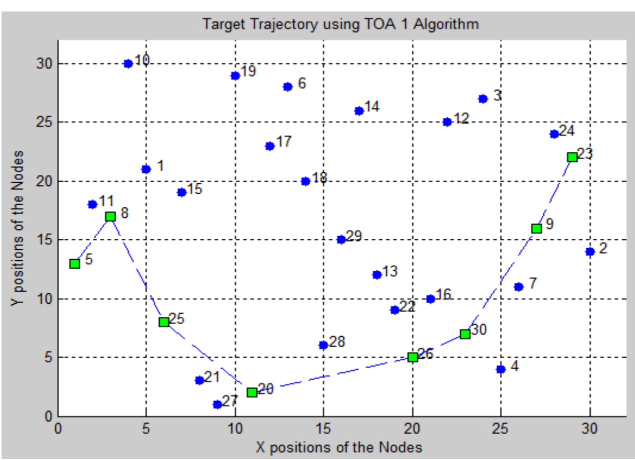

Figure 2 : Route Discovery Using TOA1

Figure 2 shows route discovery algorithm using TOA, which contains 30 nodes that are randomly placed. The source node is 8 and the target node is 23.

b) Route Discovery using TOA2 Algorithm

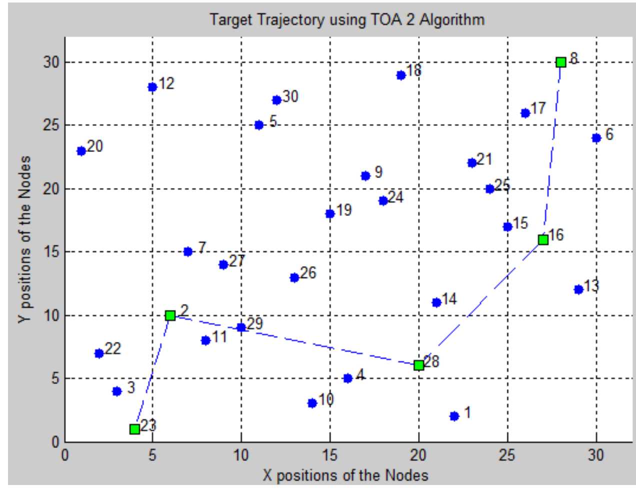

Figure 3 : Route Discovery Using TOA2

Figure 3 shows route discovery algorithm using TOA2, which contains 30 nodes that are randomly placed. TOA2 algorithm selects 3 intermediate nodes from source to destination whereas TOA1 algorithm selects 7 intermediate nodes.

c) Comparison between TOA1 and TOA2

We consider factors like Power consumption, Energy consumption, No of hops, Time for comparing the TOA algorithm and TOA2 algorithm.

No of Sensor	Source Node	Target Node	Power (mw)	Env. factor	Energy (mj)	Energy for Amp
50	23	9	1	0.5	1	0.5

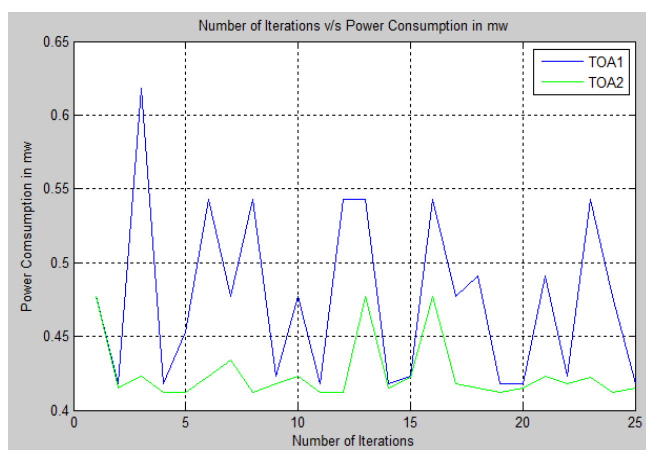

Figure 4 : No of Iteration v/s Power Consumption in mW

Figure 4 represents the graph between no. of iteration and power consumption in mw. From figure it is clear that TOA2 is having low power consumption as compared to TOA1.

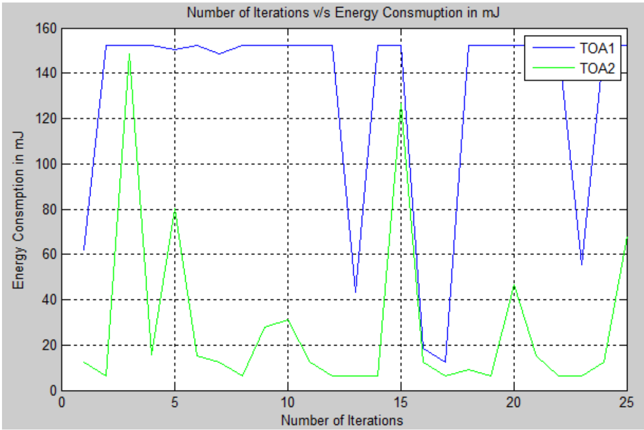

Figure 5 : No of Iteration v/s Energy Consumption in mJ

Figure 5 represents the graph between no. of iteration and energy consumption in mJ. From figure it is clear that TOA2 is having low energy consumption as compared to TOA1.

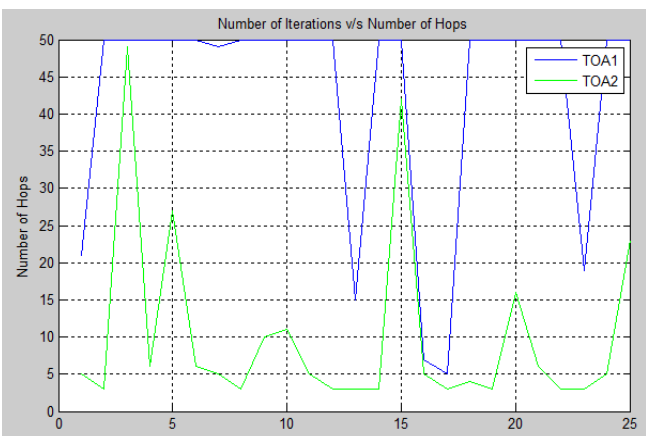

Figure 6 : No of Iteration v/s No. of Hops

Figure 6 represents the graph between no. of iteration and no of hops. No of hops is the no of links between a source node to destination node. The no of hops decreases when coverage area increases. Here the coverage area is fixed for both the algorithms. From figure 6 it is clear that TOA2 is having less no of hops as compared to TOA1.

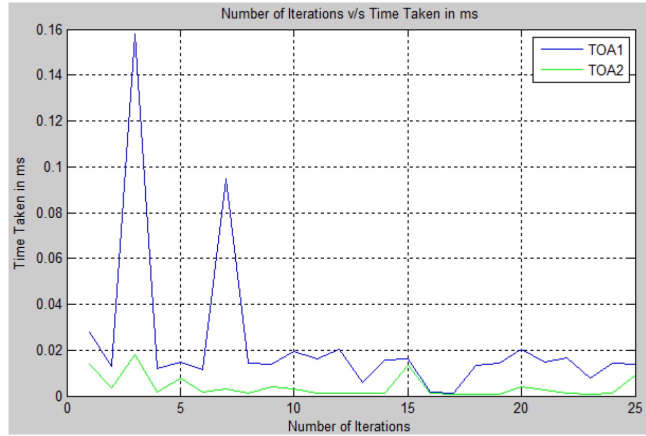

Figure 7 : No of Iteration v/s Time taken in ms

Figure 7 represents the graph between no. of iteration and time taken in ms. From figure it is clear that TOA2 takes less time as compared to TOA1.

No of Iteration/ Factor	5		10		25	
	TOA1	TOA2	TOA1	TOA2	TOA1	TOA2
Power(mw)	0.45	0.42	0.47	0.43	0.423	0.422
Energy(mj)	150	80	150	30	50	70
No of Hops	50	28	60	12	80	20
Time in Ms	.01	.005	0.02	.015	.019	.015

From the above table it is clear that the power and energy required for TOA2 algorithm is less than TOA1 algorithm. The second algorithm takes less time as compared to first one and also it takes less no hopes.

d) Comparison Filter Target Detection for Less Sensor Elements and Widely Spaced Sources

Algorithm	Number of Sensors	Target Direction	Amplitude
Kalman	20	[25 40 60]	[1 2 3]
WMA1	20	[25 40 60]	[1 2 3]
WMA2	20	[25 40 60]	[1 2 3]
CRLB	20	[25 40 60]	[1 2 3]

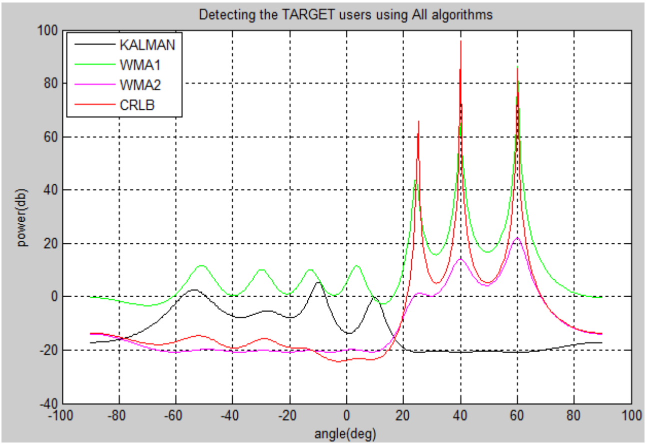

Figure 8 : Comparison of Filters for Less Sensor Elements and Widely Spaced Targets

From the plot it is evident that the Kalman filter is not able to detect target. The WMA1 and CRLB detect the target at 25, 40 and 60 degree as shown in the figure 8 .WMA2 detects two targets at 40 and 60 degree.

e) Comparison Filter Target Detection for Large Sensor Elements and Widely Spaced Sources.

Algorithm	Number of Sensors	Target Direction	Amplitude
Kalman	100	[25 40 60]	[1 2 3]
WMA1	100	[25 40 60]	[1 2 3]
WMA2	100	[25 40 60]	[1 2 3]
CRLB	100	[25 40 60]	[1 2 3]

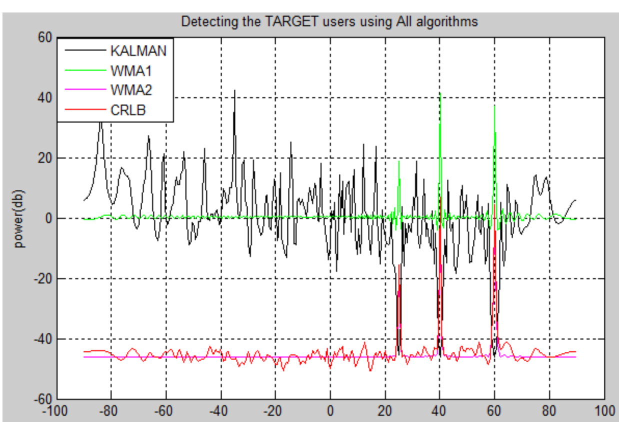

Figure 9 : Comparison of Filters for Large Sensor Elements and Widely Spaced Targets

From the plot it is evident that the WMA1 and CRLB detect the target at 25, 40 and 60 degree as shown in the figure 9. WMA2 detects the target and Kalman filter is not able to detect all the targets.

f) Comparison Filter Target Detection for Less Sensor Elements and Closely Spaced Sources

Algorithm	Number of Sensors	Target Direction	Amplitude
Kalman	20	[35 40 45]	[1 2 3]
WMA1	20	[35 40 45]	[1 2 3]
WMA2	20	[35 40 45]	[1 2 3]
CRLB	20	[35 40 45]	[1 2 3]

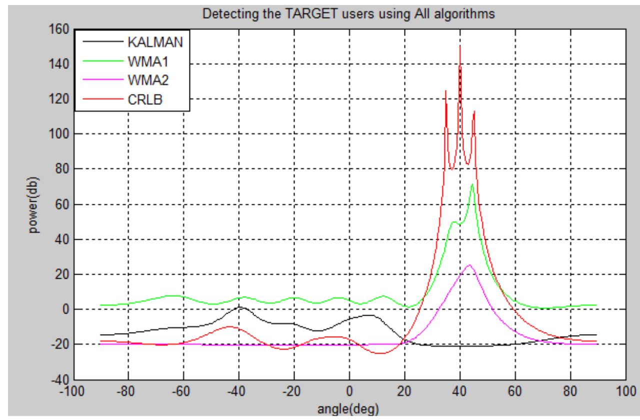

Figure 10 : Comparison of Filters for Less Sensor Elements and closely Spaced Targets

From the plot it is evident that the CRLB detect all the three targets where WMA1 detect two targets at 40 and 45 degree as shown in the figure 10. WMA2 detects one target whereas and Kalman filter is not able to detect all the targets.

g) Comparison Filter Target Detection for Large Sensor Elements and Closely Spaced Sources.

Algorithm	Number of Sensors	Target Direction	Amplitude
Kalman	100	[35 40 45]	[1 2 3]
WMA1	100	[35 40 45]	[1 2 3]
WMA2	100	[35 40 45]	[1 2 3]
CRLB	100	[35 40 45]	[1 2 3]

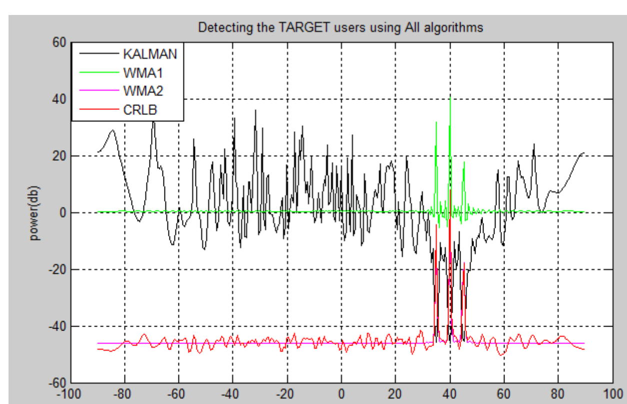

Figure 11 : Comparison of Filters for Large Sensor Elements and closely Spaced Targets

From the plot it is evident that the CRLB and WMA1 detects all the three targets as shown in the figure 11 where WMA2 also detects targets whereas and Kalman filter is not able to detect all the targets.

IX. Conclusion

From the various simulations we can find out that CRLB works best as compared to all other algorithms for various cases like Low Sensors and Widely spaced targets, Low Sensors and Closely Spaced targets, Large Sensors and Widely Spaced targets and finally large sensor and closely spaced sources. From the various simulations one can prove that the TOA2 algorithm works better as compared to TOA1 algorithm with respect to energy, time, power and no of hops.

Algorithms can be future improved by maintaining the route trace list thereby reducing the energy, time, power and number of hops.

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