An Accurate Localization Technique for Wireless Sensor Networks Using MUSIC Algorithm

A. R. Kulaib [1], R. M. Shubair [1], M. A. Al-Qutayri [1], and Jason W. P. Ng [2]
[1] College of Engineering, Khalifa University, Sharjah, UAE
Email: {akulaib, raed.shubair, mqutayri}@kustar.ac.ae
[2] Etisalat BT Innovation Centre, Abu-Dhabi, UAE
Email: jason.ng@kustar.ac.ae

***Abstract*— Wireless Sensor Networks (WSNs) are used in civilian as well as military applications to support a wide range of services. Combining sensor data with location information increases the range of applications, and the accuracy of data interpretation. There are several localization techniques that are presented in the literature. These techniques are classified into centralized and distributed depending on where the computational effort is carried out. In this paper, MUltiple SIgnal Classification (MUSIC) is used to localize the position of sensor nodes based on the intersection of different beams. Computer simulations show that the algorithm provides high localization accuracy at reasonable noise levels.**

***Index Terms*— Adaptive Beamforming, Localization, Wireless Sensor Network.**

I. Introduction

Sensor nodes usually consist of low power processor, small amount of memory, wireless transceiver, and a sensor board. The size and price of sensor nodes decreased significantly over the past few years to the point that it is possible to build large WSNs. Such networks are becoming increasingly important as they enable the placement of sensors as close as possible to the event, which in turn provides better signal quality. However, the sensor data by itself, in many applications, is of low value unless the spatial information is known. This is because; the lack of location information can result in an incorrect interpretation of data. As a result, research interest in WSN localization has recently increased significantly. WSNs are used in wide range of applications, such as habitat monitoring, smart environments, and target tracking. These applications require exact localization of nodes with respect to a global coordinate system in order to provide meaningful information and to be able to efficiently route data through the network [1], [2].

Localization is basically the process of determining the physical coordinates of a group of sensor nodes. In WSNs, nodes that have known coordinates are called beacon nodes or anchor nodes. These nodes provide their global coordinates either by hard coding it or by fitting them with a GPS receiver. Using anchor nodes simplifies the task of assigning coordinates to ordinary nodes. However, anchor nodes usually use a GPS, which is expensive, cannot be used indoor, and may face some difficulties if they are placed near obstacles such as tall buildings. The GPS also consumes significant battery power which is a limited resource in WSNs. Another option is to program the nodes with their locations before deployment. This method is impractical for large scale networks and impossible if nodes are deployed over a wide area such as those dropped from an aircraft [1]. The coordinates in a network can either be absolute (global) or relative (local). Absolute location can be obtained using anchor nodes, while relative location can be determined using signal processing techniques such as multilateration or triangulation [2], [3].

It is worth noting, that this paper is extension of the paper published in [4], and the classification of localization algorithms has been presented in [5].

This paper is organized as follows. The next section highlights some location discovery approaches, and section III classifies the localization algorithms. Then adaptive beamforming algorithms are explained in section IV. After that, the simulation results obtained from combining WSN and beamforming to pinpoint the position of sensor nodes is presented in V. Finally, section VI presents the conclusions of this study and the future directions.

II. Location Discovery Techniques

There are three basic localization techniques that are used as a base to a more advanced techniques [6], [7]:

- **Trilateration:** This method determine the position of a node from the intersection of 3 circles of 3 anchor nodes that are formed based on distance measurements between its neighbours. The radius of the circle is equal to the distance measurement as shown in Fig. 1. However, in a real environment, the distance measurement is not perfect; hence, more than three nodes are required for localization.
- **Triangulation:** This method is used when the direction of the node rather than the distance is estimated. It uses trigonometry laws of sines and cosines to calculate the nodes position based on the angle information from two anchor nodes and their positions as shown in Fig. 2.

Manuscript received January 10, 2012; accepted March 27, 2012.

doi:10.4304/jcm.7.4.281-289

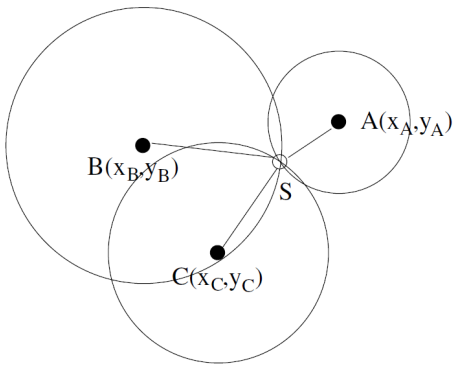


Figure 1. Trilateration technique [6].

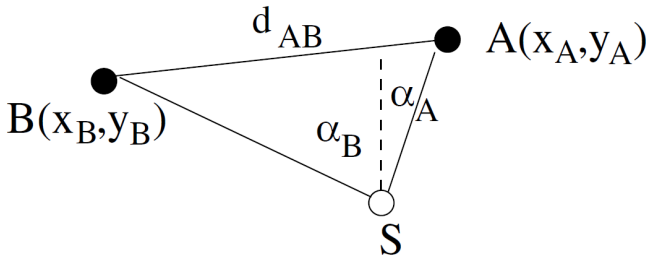


Figure 2. Triangulation technique [6].

- **Maximum Likelihood Multilateration:** Trilateration technique cannot accurately estimate the position of a node if the distance measurements are noisy. A possible solution is to use the Maximum Likelihood (ML) estimation, which includes distance measurements from multiple neighbour nodes as shown in Fig. 3. This method intends to minimize the differences between the measured distances and estimated distances.

Several localization or ranging techniques that are used to localize the position of sensor nodes have been proposed in the literature, they include *Time of Arrival* (ToA), *Received Signal Strength* (RSS), *Radio Hop Count* (RHC), and *Angle of Arrival* (AoA) [1], [3], [6], [8], [9].

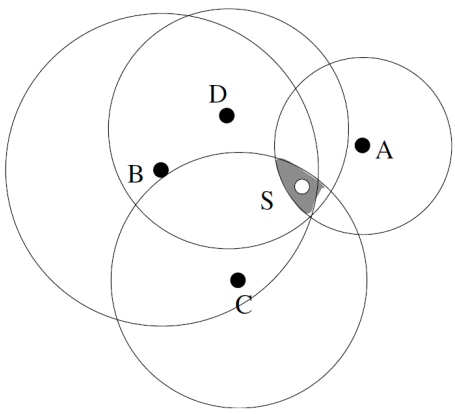


Figure 3. Multilateration technique [6].

A. Time of Arrival Technique

ToA is defined as the earliest time at which the signal arrives at the receiver. It can be measured by adding the time at which the signal is transmitted with the time needed to reach the destination (time delay). The time delay can be computed by dividing the separation distance between the nodes by the propagation velocity. In ToA, the nodes have to be synchronized and the signal must include the time stamp information [3]. To overcome these restrictions, *Round-trip Time of Arrival* (RToA) and *Time Difference of Arrival* (TDoA) are developed.

RToA is similar to ToA but it doesnot require a common time reference between nodes. It works by recording the time of transmission at node 'A' according to its own clock, then node 'B' records the reception time in its own time reference and transmits back to node 'A' after some time interval. Finally, node 'A' records the time of reception and uses the recorded timings to determine the distance between the two nodes [3].

TDoA is a well known technique to measure distance between nodes. TDoA techniques can be classified into two main types: multi-node TDoA, and multi-signal TDoA. The multi-node TDoA uses ToA measurements of signals transmitted from multiple anchor nodes. Three synchronized anchor nodes are required to accurately locate a node as shown in Fig. 4. This technique works by measuring the difference in time between a pair of anchor nodes. This difference defines a hyperbola on which node 'S' should lie. Two hyperbola are sufficient to pin point the location of node 'S'. On the other hand, the multi-signal TDoA uses two different kinds of signals that have different propagation speeds to estimate the distance to another node. This technique requires additional equipments, a microphone and a speaker. In this technique it is possible to use ultrasound or audible frequency without changing the algorithm. It operates by sending a radio message and waiting for fixed interval t_{delay} and then produces a signal with a fixed pattern (chirps) using its speaker. On the other side, a node will register the current time t_{radio} when it detects the radio signal, then turns on their microphones and waits until it detects a chirp to register the current time (t_{sound}). Finally, the distance between the two nodes is calculated using (1), that is based on the fact that sound (s_{sound}) travels significantly slower than radio (s_{radio}) waves in air as shown in Fig. 5.

$$d = (s_{radio} - s_{sound}) * (t_{sound} - t_{radio} - t_{delay}) \quad (1)$$

TDoA can also be measured based on the fact that the distances between the transmitter and different receivers are different. This means that the transmitted signal is delayed in time based on the distance to the receiver. The time delay between two receivers can be obtained by computing the correlation between the two signals. The location of the peak in the cross correlation output is used to estimate the TDoA. Moreover, it is recommended

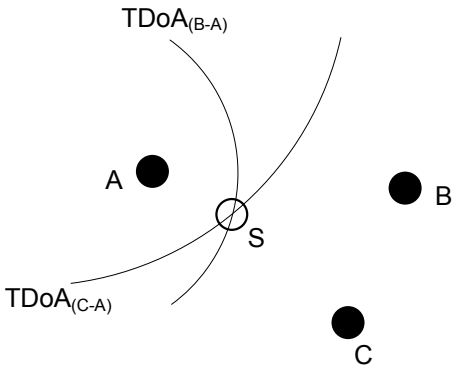


Figure 4. Multi-node time difference of arrival method.

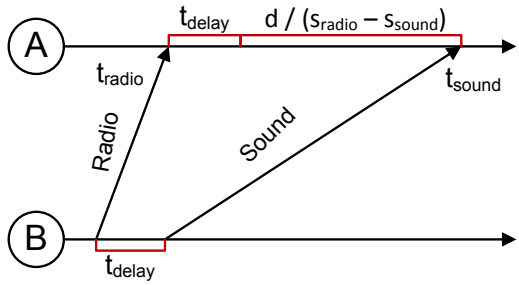


Figure 5. Multi-signal time difference of arrival method.

to use the generalized cross correlation, since it is less vulnerable to noise, interference, and multipath [10].

B. Received Signal Strength Technique

RSS is a common technique in localizing sensor nodes; this is due to the fact that almost all nodes have the ability to measure the strength of the received signal. RSS technique benefits from the fact that radio signals diminish with the square of the distance from the signal's source. In other words, the node can calculate its distance from the transmitter using the power of the received signal, knowledge of the transmitted power, and the path-loss model. The operation starts when an anchor node broadcasts a signal that is received by the transceiver circuitry and passed to the Received Signal Strength Indicator (RSSI) to determine the power of the received signal. The RSS measurements of node i and j at time t can be calculated using the following equation [6]:

$$P_R^{ij}(t) = P_T^i - 10\eta \log(d_{ij}) + X_{ij}(t) \qquad (2)$$

where P_T^i is a constant due to the transmitted power and the antenna gains of the sensor nodes, η is the attenuation constant, d_{ij} is the distance between the two nodes, and $X_{ij}(t)$ is the uncertainty factor due to multi-path and shadowing.

In addition, a technique similar to RSS called potentiometer can be used for sensor localization. This technique works by increasing the signal power in steps until the node receives three replies. Then it sends the data to a central receiver to compute the position of the sensor node using triangulation [11].

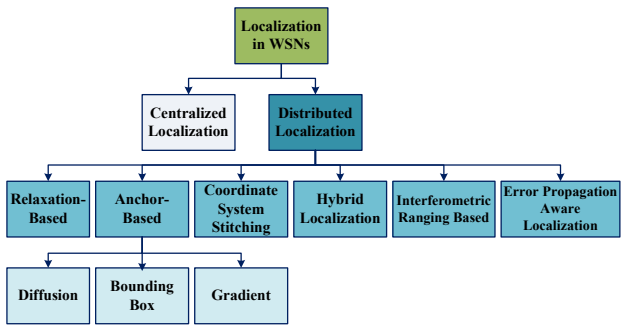


Figure 6. Classification of WSN localization algorithms.

C. Radio Hop Count Technique

RHC technique exploits the fact that if two nodes can communicate then the distance separating them is less than R, where R is the maximum range of their radios. For instance, if s_i and s_j are two nodes in a network then h_{ij} is the hop count that represents the shortest path between the two nodes, and d_{ij} is the distance between the two nodes, which is less than Rh_{ij}. In order to get a better estimate of the distance (3) is used if the expected number of neighbours per node is known (n_l) and is between 5 and 15. Above 15 nodes d_h approaches R, Thus, d_{ij} becomes approximately equal to $h_{ij}d_h$ [1].

$$d_h = R\left(1 + e^{-n_l} - \int_{-1}^{1} e^{-\frac{n_l}{\pi}(acos\ t - t\sqrt{1-t^2})} dt \right) \qquad (3)$$

D. Angle of Arrival Technique

AoA technique can obtain angle data using radio array methods. It can estimate the AoA using multiple or directional antennas. In multiple antennas, it operates by analysing the time or phase difference between the signals at different array elements that have known locations with respect to the centre element. For example, the difference in arrival time Δ_t between two antenna elements is formulated in (4), where δ is the antenna separation, v is the velocity of the RF signal, and θ is the angle at which the signal arrives. In directional antennas, it operates by computing the RSS ratio between several directional antennas that are placed carefully, in order to have an overlap between their main beams. The AoA measurement from two anchor nodes can be combined with their locations (tringulation) to estimate the location of the node [3], [8].

$$\Delta_t = \delta/(v\ \cos\ \theta) \qquad (4)$$

An alternative method is the beamforming technique that is used in array signal processing and is described in section IV.

III. Classification of Localization Algorithms

Localization algorithms can be classified based on different criteria, such as single-hop vs. multi-hop, anchor

vs. non-anchor, centralized vs. distributed *etc*. In this paper the localization algorithms are categorized into two main types, namely centralized and distributed algorithms as in Fig. 6 [1], [7].

A. Centralized Algorithms

Centralized algorithms require plenty of computational po-wer in order to run their operations on central machines. This high amount of computational power enables the algorithms to execute complex mathematical operations. This advantage comes with a communication cost, since all sensor nodes in the network will send their data to the central receiver and computed positions are sent back to respective nodes. There are different types of centralized algorithms depending on the way they process data at the central receiver. Such algorithms include *Semidefinite Programming* (SDP) [12] and *Multi-dimensional Scaling* (MDS) [13]. This paper concentrates on distributed algorithms as they are considered more efficient than centralized ones.

B. Distributed Algorithms

Distributed algorithms run their operations using the computational power of each node. This type requires massive inter-node communication and parallelism to be able to perform similar to centralized systems. Distributed algorithms can be divided into six main groups, which are *anchor-based*, *relaxation-based*, *coordinate system stitching*, *hybrid localization*, *interferometric ranging based localization*, and *error propagation aware localization* algorithms.

The first group is the *anchor-based* distributed algorithms. As the name implies, this type of algorithm uses anchors to find the position of unknown nodes. The nodes start by obtaining a distance measurement to few anchors and then determines their location based on these measurements. There are several anchor-based algorithms in the literature, such as *diffusion* [14], *bounding box* [15], *gradient* [16], and *Approximate Point In Triangle* (APIT) [17] algorithms.

The *diffusion* algorithm [14] is a simple algorithm that only uses radio connectivity data. It assumes that the node is most probably at the centroid of its neighbours' positions. There are two different alternatives to this algorithm. The first option developed by Bulusu *et al* [18] averages the positions of all anchors that can communicate with the node using radio, in order to localize the position of that node. The second option developed in [14] considers both anchors and normal nodes in determining the position of the node at centre. The advantage of the algorithm in [14] is that it requires fewer anchors than the one in [18].

The *bounding box* algorithm [15] calculates the position of the node based on the ranges to several anchors. Each anchor has a box and the intersection between these boxes determines the position of the node as shown in Fig. 7. The box of an anchor is placed at the centre of the anchor position. Its size depends on the distance between the node and the anchor, where the width and height is twice the distance between the node and the anchor. This algorithm is used when sensor nodes cannot perform a lot of computation, and when the node is close to the centre of their anchors, since the accuracy is higher in such situation.

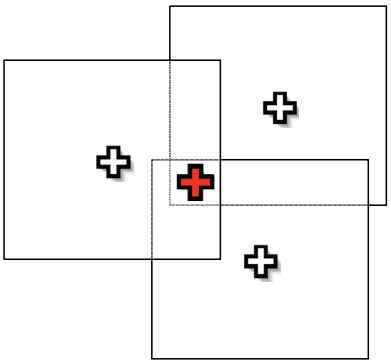


Figure 7. An example of the intersection of bounding boxes.

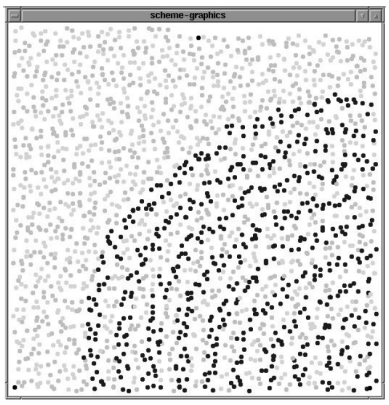


Figure 8. Gradients propagation of one anchor placed at the lower right corner [1].

Another approach is the *gradient* algorithm [16] which starts by sending a message from anchor nodes to their neighbours. This message contains the anchor position and a count set to one. Then each node will send the same message to it neighbours after incrementing the counter. After that each node will keep the lower counter value and will use it to calculate the estimated distance using radio hop count technique. Finally, multilateration is used to compute the position of each node by combining the estimated distance from all anchor nodes. The gradient propagation of one anchor is shown in Fig. 8, where each dot represents a node, and the color of the node represents its gradient value. This algorithm can easily adapt to the addition or death of normal nodes or anchors. However, it requires substantial node density to reach an acceptable accuracy level.

A different approach is the APIT algorithm [17] that is based on an area approach which forms triangles of arbitrary anchors. Each node selects three anchors in its radio coverage area, and then decides if it is inside or outside the triangle based on signal strength

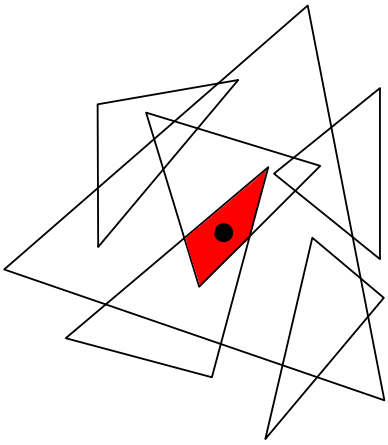


Figure 9. Illustartion of Approximate Point In Triangle (APIT).

measurements with nearby non-anchor neighbours. After testing all triangle combinations, the node position is the centroid of the intersection region of the anchor triangles as shown in Fig. 9. The advantage of this algorithm is that it requires smaller amounts of computation and less communication when compared to other anchor based algorithms. However, it requires longer range anchors, relatively high ratio of anchors to nodes, and RSS has to be calibrated.

The second group is *relaxation-based* distributed algorithms [19]. This group fuses the computational advantages of distributed schemes with the precision of centralized schemes. It starts by estimating the position of the nodes using one of the above distributed techniques. Then the positions are refined from position estimates of their neighbours, which are considered temporary anchors. The refining step is performed using local neighbourhood multilateration or an equivalent technique called the spring model [20], which represents distance between nodes with resting springs. It uses an optimization technique that will change nodes position in every iteration, until all nodes have zero forces acting on them. The advantages of this algorithm is its ability to operates without anchors, it is fully distributed, and concurrent. However, it cannot guarantee avoiding local minima, especially in larger scale networks.

The third group is *coordinate system stitching* algorithms [21]. It consists of three main steps. The first step is to split the network into small overlapping subregions which are usually a single node and its one-hop neighbours. In the second step a local map of each subregion is computed. Finally, the third step places all the subregions into a single global coordinate system using a registration procedure. The first two steps in this process differ between one algorithm and another while the third step is common for all.

The fourth group is *hybrid localization* algorithms. It simply combines two existing techniques to get a better performance, such as using both multidimensional scaling and proximity based map [22].

The fifth group is *interferometric ranging based localization* algorithms. It works by creating an interference signal using two transmitters emitting radio waves simultaneously at slightly different frequencies. The signal will arrive at the two receivers with a phase offset, which is a function of the relative positions of four nodes. The advantage of this algorithm over other algorithms is its high accuracy with long range measurements, but it requires a considerably larger set of measurements, thus it is limited to small networks [23].

Finally, the *error propagation aware localization* is important since error propagation can degrade the performance of an algorithm. There are two types of error, range and position error. Combining information about error characteristic with the algorithm can result in increasing the accuracy and the robustness of the algorithm. The basic idea of the algorithm is that nodes use the available information to transform into anchors in an iterative method, taking in consideration the minimization of position error and error propagation. The advantage of this algorithm is that it is more precise than other localization schemes, since its uses ranging and position information obtained from each involved anchor [24].

IV. Adaptive Beamforming Algorithms

Beamforming is a technique used in array signal processing for a wide range of applications such as radar, sonar, communications, medical imaging, astronomy, and acoustics [25]. Beamforming uses spatial filters to form beams, hence the name. The beamformer is used to perform spatial filtering to separate signals that have overlapping frequency contents but originate from different spatial locations [26]. There are two main types of beamformers; data-independent and data-dependent, the latter is called adaptive beamformers. The difference between the two methods is that weight vectors in adaptive beamformers are selected as a function of data. The adaptive beamformers are widely used, because they can have better resolution and can reject interference [25]. The operation of an adaptive filter is based on a recursive algorithm, which enables the filter to perform well in environment where relevant signal characteristics are not completely known. Initially the recursive algorithm starts with initial conditions that are determined according to the information that is known about the environment. If the environment is stationary the recursive algorithm will settle down after some iteration. However if the environment is non-stationary, the algorithm provides a tracking capability, where it can track variations in time in the statistics of the input data, if the variations are adequately slow [27].

The choice of an adaptive algorithm depends on many factors such as the cost of the system, computational cost, performance, and robustness. It also depends on the application and the environment. Thus, the solution for one application may not be suitable for another. Therefore, it is recommended to study the environment before selecting or developing a new algorithm [27]. A general block diagram of the adaptive beamformer is

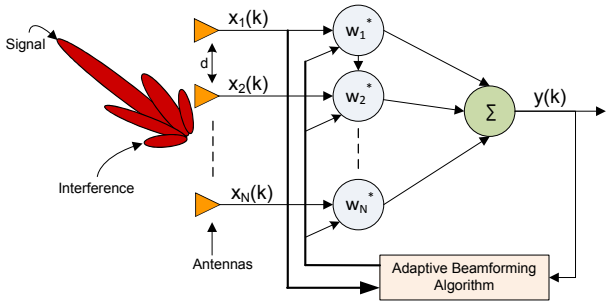


Figure 10. Adaptive beamformer block diagram.

shown in Fig. 10. The beamformer output is represented by [26]:

$$\mathbf{y}(k) = \sum_{l=1}^{N} \mathbf{w}_l^* \mathbf{x}_l(k) \tag{5}$$

where $\mathbf{w}$ is an N dimensional weight complex vectors (N is the number of antennas), and $\mathbf{x}(k)$ is the array snapshot with time index k.

In this study, *MUltiple SIgnal Classification* (MUSIC) algorithm proposed by Schmidt [28] is used to detect the direction of the incident signal. The MUSIC angular or spatial spectrum is defined as:

$$P(\theta) = \frac{\mathbf{a}(\theta)^H \mathbf{a}(\theta)}{\mathbf{a}(\theta)^H \mathbf{V}_n \mathbf{V}_n^H \mathbf{a}(\theta)} \tag{6}$$

where matrix $\mathbf{A}$ contains the steering vectors $\mathbf{a}(\theta)$, and $\mathbf{V}_n$ is the matrix of eigenvectors corresponding to the noise subspace of matrix $\mathbf{R}$ (covariance matrix):

$$\hat{\mathbf{R}} = \frac{1}{K} \sum_{k=1}^{K} \mathbf{x}(k)\mathbf{x}(k)^H \tag{7}$$

where $(\bullet)^H$ denotes the Hermitian function.

Orthogonality between $\mathbf{V}_n$ and $\mathbf{a}$ minimizes the denominator which in turn gives rise to peaks in the MUSIC spectrum. Those peaks will correspond to the directions of arrival of the signals impinging on the sensor array.

MUSIC algorithm has a high storage and computational load requirements due to the exhaustive search through all possible steering vectors to estimate the directions of arrival. Other versions of the MUSIC algorithm have been introduced to reduce the storage and computational load requirements, such as Root MUSIC and *Estimation of Signal Parameters via Rotational Invariance Technique* (ESPRIT). In addition, *Minimum Variance Distortionless Response* (MVDR) beamformer with *Variable Loading* (VL) can be used at the receiver side to direct the beam toward the target and reduce the consumed power [29].

The optimal MVDR beamformer is based on the following criterion: $\min_{\mathbf{w}} \mathbf{w}^H \mathbf{R} \mathbf{w}$ subject to $\mathbf{w}^H \mathbf{v}_0 = 1$, which leads to the following solution:

$$\mathbf{w}_{opt} \triangleq \frac{\mathbf{R}^{-1}\mathbf{v}_0}{\mathbf{v}_0^H \mathbf{R}^{-1} \mathbf{v}_0} \tag{8}$$

where $\mathbf{R}$ is an $N \times N$ complex matrix (covariance matrix) of $\mathbf{x}(k)$, and $\mathbf{v}_0$ is the nominal steering vector. $\mathbf{v}_0$ is usually replaced by the estimated steering vector in practice:

$$\mathbf{v} = \mathbf{v}_0 + \mathbf{e} \tag{9}$$

where $\mathbf{e}$ is the error vector due to array perturbations and AoA mismatch. The error $\mathbf{e}$ is assumed to be an independent complex Gaussian with zero mean and variance (σ_e^2).

Replacing the inverse of the covariance matrix $\mathbf{R}^{-1}$ in (8) by $\hat{\mathbf{R}}^{-1}$ leads to the SMI weight vector in (10). $\hat{\mathbf{R}}$ is calculated by averaging the outer product of K snapshots as in (7).

$$\mathbf{w}_{SMI} \triangleq \frac{\hat{\mathbf{R}}^{-1}\mathbf{v}}{\mathbf{v}^H \hat{\mathbf{R}}^{-1} \mathbf{v}} \tag{10}$$

$\hat{\mathbf{R}}^{-1}$ is not a good substitute for $\mathbf{R}^{-1}$; especially when $K < N$. The is due to the fact that $\hat{\mathbf{R}}$ is not a full rank and hence cannot be inverted directly. This problem can be solved by modifying the sample covariance matrix to be diagonally loaded ($\hat{\mathbf{R}} + \gamma \mathbf{I}$) by a loading level $\gamma > 0$, which is calculated to satisfy the quadratic constraint with equality $\|\mathbf{w}\|^2 \leq T$. As a result, the optimization and the weighting vector are modified as:

$$\min_{\mathbf{w}} \mathbf{w}^H \hat{\mathbf{R}} \mathbf{w} \quad \text{subject to} \quad \mathbf{w}^H \mathbf{v} = 1, \quad \|\mathbf{w}\|^2 \leq T \tag{11}$$

where T is the quadratic norm threshold.

$$\mathbf{w}_{DL} \triangleq \frac{(\hat{\mathbf{R}} + \gamma \mathbf{I})^{-1}\mathbf{v}}{\mathbf{v}^H (\hat{\mathbf{R}} + \gamma \mathbf{I})^{-1} \mathbf{v}} \tag{12}$$

However, in VL the norm of the weighting vector is constrained according to $\mathbf{w}^H \hat{\mathbf{R}}^{-1} \mathbf{w} \leq T'$. As a result, the optimization problem is modified as:

$$\min_{\mathbf{w}} \mathbf{w}^H \hat{\mathbf{R}} \mathbf{w} \quad \text{subject to} \quad \mathbf{w}^H \mathbf{v} = 1, \quad \mathbf{w}^H \hat{\mathbf{R}}^{-1} \mathbf{w} \leq T' \tag{13}$$

VL levels for the eigenvalues of $\hat{\mathbf{R}}$ is formed due to the difference in this quadratic constraint. Consequently, the weighting vector is modified as:

$$\mathbf{w}_{VL} = \frac{(\hat{\mathbf{R}} + \delta \hat{\mathbf{R}}^{-1})^{-1}\mathbf{v}}{\mathbf{v}^H (\hat{\mathbf{R}} + \delta \hat{\mathbf{R}}^{-1})^{-1} \mathbf{v}} = \frac{(\hat{\mathbf{R}}^2 + \delta \mathbf{I})^{-1} \hat{\mathbf{R}} \mathbf{v}}{\mathbf{v}^H (\hat{\mathbf{R}}^2 + \delta \mathbf{I})^{-1} \hat{\mathbf{R}} \mathbf{v}} \tag{14}$$

where δ is the VL level ($\delta = \gamma^2$). The parameter δ is calculated so that $\mathbf{w}^H \hat{\mathbf{R}}^{-1} \mathbf{w} = T'$.

The Diagonal Loading (DL) technique induces a tradeoff between the ability of the beamformer to adaptively cancel interference and reduce noise as well as sidelobe suppression. For instance, when the loading value is too large, the beamformer fails to suppress strong interferences, since it concentrates on suppressing white noise. On the other hand, VL performance and robustness is better than DL, because it has the ability to load the

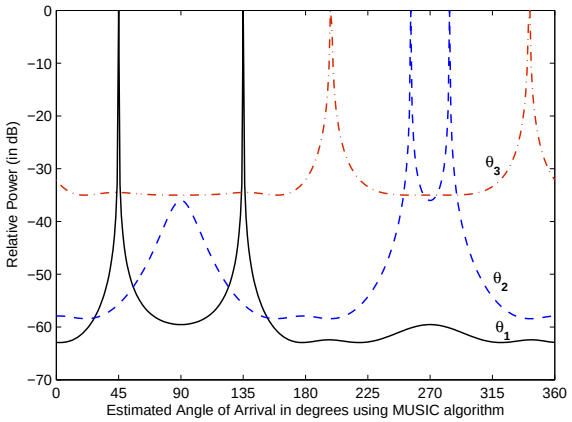


Figure 11. Estimated AoA in degrees using MUSIC algorithm for three different angles

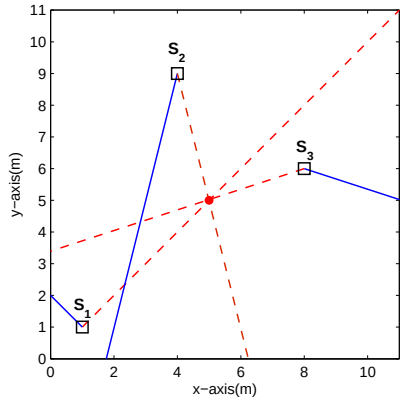


Figure 12. WSN localization using MUSIC (*SNR*=20dB). Desired node location is determined by the largest number of intersections

eigenvalues of the covariance matrix depending on their magnitudes, with lesser loading for large eigenvalues and greater loading for small eigenvalues.

V. Simulation Results

A WSN environment is modelled in Matlab, where any number of sensor nodes can be placed randomly in an environment whose size can be specified by the user. This code has been combined with the MUSIC algorithm. This step enables the system to detect the position of sensor nodes from the intersection between various beams. However, an ambiguity can occur when two sensors are on the same line. This problem can be either solved by using circular antenna array or by increasing the number of sensor nodes used for localization.

To test the algorithm, each sensor node is assumed to have three antennas that forms a linear antenna array. These antennas are separated equally by 0.5λ where $\lambda = c/f$ ($c = 3 \times 10^8$ & $f = 1 \times 10^9$). The number of snapshots/samples taken for the incoming signals is set to 50. The algorithm is tested under different Signal to Noise Ratio (SNR) levels. At *SNR*=$20dB$, the AoA is measured accurately, which in turn result in an accurate sensor node localization. The system can still work in an acceptable manner when the *SNR* is reduced to $0dB$. However, lowering the *SNR* to lower levels can make the sensor node localization process more difficult, since the AoA measurement is affected by high levels of noise.

Four sensor nodes are placed randomly in an environment. The selected target is represented with a red dot, while the black squares represent the other sensor nodes. These sensor nodes receives a signal from the target which is processed using MUSIC algorithm to determine the direction of the target. Fig. 11 shows the relative power in dB versus the estimated AoA in degree for three angles ($\theta_1, \theta_2,\ and\ \theta_3$) which represent the direction of the target with respect to the sensor nodes that are represented with squares as shown in Fig. 12, 13, and 14. The AoA measurement, is used to draw a line from the sensor node toward the target. Two lines (solid and dotted) are

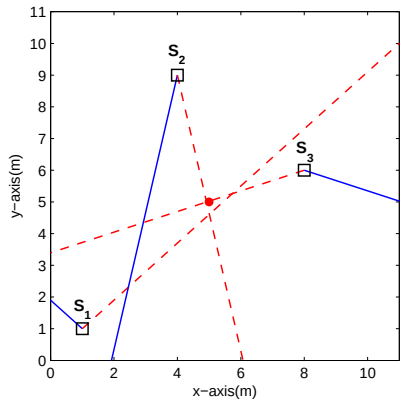


Figure 13. WSN localization using MUSIC (*SNR*=0dB). Desired node location is determined by the largest number of intersections

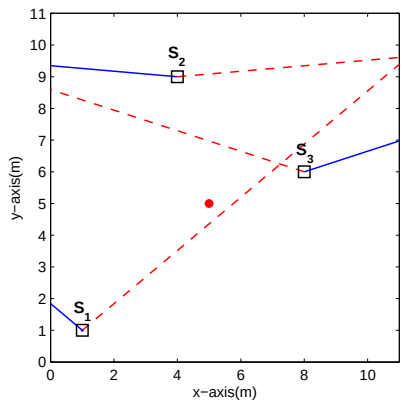


Figure 14. WSN localization using MUSIC (*SNR*=-20dB). Desired node location is determined by the largest number of intersections

drawn from each sensor node, due to the symmetry of the antenna geometry. Fig. 12, 13, and 14 shows the effect of reducing the *SNR* level on the performance of the algorithm. In these figures, there are intersections at points that have no sensors. However, the points that have more intersections will have a higher probability of node availability.

VI. Conclusions

Localization is an important aspect of WSNs as many applications use such information to deliver their services. The performance of any localization algorithm is affected by several factors such as the amount of resources available in the network (e.g. memory, processing power, and battery life), the nodes density, the shape of the network, and the environment where sensor nodes are going to be deployed. Therefore, it is important to study all those factors before designing the algorithm. In this study, a MUSIC algorithm has been implemented and used to localize a group of sensor nodes that are randomly placed in an environment. This algorithm requires at least three antennas to be able to localize the direction of the transmitted signal accurately, and steer the beam toward it. However, most sensor nodes provide only one antenna. A possible solution to this problem is to form antenna arrays from the different sensor nodes. This will be investigated in the further work.

References

[1] I. Stojmenovic, *Handbook of sensor networks: algorithms and architectures*. John Wiley and Sons, Oct. 2005.

[2] C. Raghavendra, K. Sivalingam, and T. Znati, *Wireless Sensor Networks*. Kluwer Academic, July 2004.

[3] H. Wymeersch, J. Lien, and M. Win, "Cooperative localization in wireless networks," *Proceedings of the IEEE*, vol. 97, no. 2, pp. 427–450, 2009.

[4] A. R. Kulaib, R. M. Shubair, M. A. Al-Qutayri, and J. W. P. Ng, "Robust localization techniques for wireless sensor networks using adaptive beamforming algorithms," *27th International confrence in Applied Computational Electromagnetics*, 2011.

[5] A. R. Kulaib, R. Shubair, M. Al-Qutayri, and J. W. P. Ng, "An overview of localization techniques for wireless sensor networks," *Innovations in Information Technology*, 2011.

[6] I. Akyildiz and M. Vuran, *Wireless Sensor Networks*. John Wiley & Sons Inc, Aug. 2010.

[7] A. Pal, "Localization algorithms in wireless sensor networks: Current approaches and future challenges," *Network Protocols and Algorithms*, vol. 2, no. 1, pp. 45–74, 2010.

[8] N. Patwari, J. Ash, S. Kyperountas, A. Hero, R. Moses, and N. Correal, "Locating the nodes: cooperative localization in wireless sensor networks," *IEEE Signal Processing Magazine*, vol. 22, no. 4, pp. 54–69, 2005.

[9] G. Mao, B. Fidan, and B. Anderson, "Wireless sensor network localization techniques," *Computer Networks*, pp. 2529–2553, 2007.

[10] F. Gustafsson and F. Gunnarsson, "Positioning using time-difference of arrival measurements," *ICASSP*, vol. 6, pp. 553–556, 2003.

[11] M. Terwilliger, "Localization in wireless sensor networks," Ph.D. dissertation, Western Michigan University, Kalamazoo, MI, USA, 2006.

[12] L. Doherty, K. Pister, and L. Ghaoui, "Convex position estimation in wireless sensor networks," *Twentieth Annual Joint Conference of the IEEE Computer and Communications Societies*, vol. 3, pp. 1655–1663, 2001.

[13] Y. Shang, W. Ruml, Y. Zhang, and M. Fromherz, "Localization from mere connectivity," *Proceedings of the 4th ACM international symposium on Mobile ad hoc networking & computing*, pp. 201–212, 2003.

[14] S. Fitzpatrick and L. Meertens, "Diffusion based localization," *private communication*, 2004.

[15] S. Simic and S. Sastry, "Distributed localization in wireless ad hoc networks," *University of California Technical Report*, 2002.

[16] J. Bachrach, R. Nagpal, M. Salib, and H. Shrobe, "Experimental results for and theoretical analysis of a self-organizing global coordinate system for ad hoc sensor networks," *Telecommunication Systems*, vol. 26, no. 2, pp. 213–233, 2004.

[17] T. He, C. Huang, B. Blum, J. Stankovic, and T. Abdelzaher, "Range-free localization schemes for large scale sensor networks," *Proceedings of the 9th annual international conference on Mobile computing and networking*, pp. 81–95, 2003.

[18] N. Bulusu, V. Bychkovskiy, D. Estrin, and J. Heidemann, "Scalable, ad hoc deployable rf-based localization," 2002.

[19] C. Savarese, J. Rabaey, and J. Beutel, "Locationing in distributed ad-hoc wireless sensor networks," *ICASSP*, vol. 4, pp. 2037–2040, 2001.

[20] N. Hari, H. Balakrishnan, E. Demaine, and S. Teller, "Anchor-Free distributed localization in sensor networks," *MIT Laboratory for Computer Science, Technical Report*, 2003.

[21] D. Moore, J. Leonard, D. Rus, and S. Teller, "Robust distributed network localization with noisy range measurements," *Proceedings of the 2nd international conference on Embedded networked sensor systems*, pp. 50–61, 2004.

[22] K. Cheng, K. Lui, and V. Tam, "Localization in sensor networks with limited number of anchors and clustered placement," *IEEE Wireless Communications and Networking Conference*, pp. 4425–4429, 2007.

[23] N. Patwari and A. Hero, "Indirect radio interferometric localization via pairwise distances," *Proceedings of 3rd IEEE Workshop on Embedded Networked Sensors*, pp. 26–30, 2006.

[24] N. Alsindi, K. Pahlavan, and B. Alavi, "An error propagation aware algorithm for precise cooperative indoor localization," *IEEE Military Communications Conference*, pp. 1–7, 2006.

[25] J. Li and P. Stoica, *Robust Adaptive Beamforming*. Hoboken, NJ: John Wiley, 2006.

[26] B. V. Veen and K. Buckley, "Beamforming: a versatile approach to spatial filtering," *IEEE ASSP Magazine*, vol. 5, no. 2, pp. 4–24, Apr. 1988.

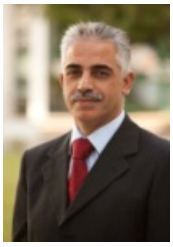
[27] S. Haykin, *Adaptive Filter Theory*, 4th ed. Prentice Hall, Sept. 2001.

[28] R. Schmidt, "Multiple emitter location and signal parameter estimation," *IEEE Transactions on Antennas and Propagation*, vol. 34, no. 3, pp. 276–280, 1986.

[29] J. Gu and P. Wolfe, "Robust adaptive beamforming using variable loading," *Fourth IEEE Workshop on Sensor Array and Multichannel Processing*, pp. 1–5, 2006.

Ahmed Kulaib earned a B.Eng degree in Electronic Engineering at Khalifa University in 2007. His senior graduation project was entitled determination of fresh concrete water-to-cement ratio using monopole probes at microwave frequencies. Soon after graduation he continued his higher education in the same university, and he was awarded an M.Sc. by research degree in 2009. His master project was in the area of acoustics, where binaural microphones were used to localize the position of a sound source. Recently he started his PhD degree in the field of Wireless Sensor Networks specifically in array signal processing. He is currently a Ph.D. student and a teaching assistant at Khalifa university since Sept 2009. He has several publications in referenced international conferences. Mr. Kulaib is an IEEE student member since 2004.

Raed Shubair received his B.Sc. degree with Distinction and Class Honors from Kuwait University, Kuwait, in June 1989 and his Ph.D. degree with Distinction from the University of Waterloo, Canada, in February 1993, both in Electrical Engineering. From March 1993 to August 1993 he was a Postdoctoral Fellow at the Department of Electrical and Computer Engineering, University of Waterloo, Canada. In August 1993 he joined Khalifa University of Science, Technology and Research (formerly Etisalat University College), UAE, where he is currently an Associate Professor at the Communication Engineering Department and Leader of the Communication & Information Systems Research Group. His current research interests include adaptive array and multi-channel processing, smart antennas and MIMO systems, as well as applied and computational electromagnetic modelling of RF and microwave circuits for wireless communications. He has published over 80 papers in refereed technical journals and international conferences. He has been a member of the technical program, organizing, and steering committees of numerous international conferences and workshops. He organized and chaired a number of technical sessions in international conferences including IEEE Symposium on Antenna and Propagation (AP-S), IEEE Symposium on Electronics, Circuits and Systems (ICECS), Progress in Electromagnetics Research Symposium (PIERS), and Applied Computational Electromagnetics Symposium (ACES). Dr. Shubair was elevated to IEEE Senior Member grade back in 2001. He was honoured by the Applied Computational Electromagnetics Society (ACES) for his valuable contributions to the ACES society in 2005. In recognition of his distinguished research record, Dr. Shubair was elected to become Fellow of MIT Electromagnetics Academy in 2007. Dr. Shubair received several research grants and scholarships from Canada National Science and Engineering Research Council (NSERC), Canada National Research Council (NRC), and Ontario Graduate Scholarship (OGS). Dr. Shubair is a founding member of the IEEE UAE Signal Processing and Communications Joint Societies Chapter as well as IEEE UAE Engineering in Medicine and Biology Society Chapter. He currently acts as Symposium Vice-Chair of the 2008 IEEE Canadian Conference on Electrical and Computer Engineering: Communications and Networking Symposium. Dr. Shubair is Editor for the Journal of Communications, Academy Publisher. He is listed in Who's Who in Electromagnetics and in several editions of Who's Who in Science and Engineering.



Mahmoud Al-Qutayri received the B.Eng degree from Concordia University, Montreal, Canada, the M.Sc. degree from University of Manchester, U.K., and the Ph.D. degree from the University of Bath, U.K., all in electrical and electronic engineering in 1984, 1987, and 1992, respectively. From 1992 to 1996, he was a Senior Lecturer at DeMontfort University, Leicester, U.K. He subsequently joined Khalifa University (formerly Etisalat College of Engineering), Sharjah, UAE, where he is currently a Professor in the Department of Electrical and Computer Engineering. He has published numerous technical papers in international journals and conferences in his fields of research, which include application of reconfigurable computing to signal processing systems, smart embedded systems, and design and test of mixed-signal integrated circuits. Prof. Al-Qutayri is a senior member of the IEEE and a member of the IET, and holds the Chartered Engineer status from the U.K. Engineering Society.

Jason Ng is a Chief Researcher in EBTIC, a joint research and innovation centre between BT, ETISALAT and KUSTAR. He joined BT in 2004, within the Pervasive ICT centre under BT Group CTO. Jason received his PhD from the Imperial College of Science, Technology and Medicine, and MBA (Distinction) from the Warwick Business School. Jason has recently authored a leading research book, entitled Space-Time Array Communications, aimed at bridging the knowledge gap in the advances of smart wireless communications. He was the inventor for the low-cost disposable RFIT (Radio Frequency Identification and Tracking) technology, which was transferred to CET Technologies Ltd for commercialisation; the pioneer for the Neurodynamics UWB system, which was spun-off as a company named Cellonics Incorporated; and the innovator for the Telecare intelligence platform, which has been trialled and implemented via Liverpool Direct Limited a joint venture between BT and Liverpool City Council. Jason has received a number of awards in recognition of his outstanding scholastic achievements and technological breakthroughs proposed in his fields of research. He holds a number of patents and publications, and was the author of several notable software packages. Jason is involved in the lecturing, tutoring and supervision for the PhD/MBA/MSc programmes. He is also actively involved in technical chairs, technical program committees, and review panels for international conference and journal publications, and is in the project review commission for the Swiss-Indian cross-governments co-operative research. Jason is a fellow of IET, a senior member of IEEE, and a Chartered Engineer (CEng).