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OPTIMAL TARGET DETECTION AND TRACKING VIA WSN NETWORKS

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OPTIMAL TARGET DETECTION AND TRACKING VIA WSN NETWORKS

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SUPERVISOR CERTIFICATION

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ABSTRACT

Recent developments in low-cost sensor technology have made Wireless Sensor Networks (WSNs) more widely applicable. One potential application of WSN is target detection and tracking. Each sensor node in a WSN runs on a battery, which is a limited and non-renewable source of energy. As a result, enhancing energy efficiency is essential because it affects the network's lifespan. This thesis presents models to reduce the consumed energy and extend the network lifetime by utilizing a Compressed Sensing (CS) approach for multi-target detection and tracking. The proposed algorithm fuse the information of all targets and sent them in one pack to the Base Station (BS) to achieve low energy consumption per sensor and reduce the number of bits sent as well as transmission processes over the network, and this led to extends the lifetime of the limited-energy sensors in the WSN. In practical sensors, the sensor readings are reported for targets within the detection range, and targets outside this range are not detected. So, We study the effect of the practical sensors on the detection process using CS. In tracking, another solution to reduce energy consumption for multi-target tracking. The K-Nearest Neighbors (KNN) algorithm is utilized to select a subset of the sensors based on the target's location to save energy and reduction of the search area for the sensors to be activated for future predictions. A Kalman Filter (KF) is used to predict the trajectories of the moving targets. The results for multi-target detection, obtained via Monte Carlo simulations, show that the proposed approach presents substantial energy reduction without compromising target detection accuracy for a relatively large number of targets, and the practical proposed approach performs better than the ideal case. The results for multi-target tracking demonstrate that our tracking scheme can track multiple targets effectively, reduces the search area for future prediction, and reduce the energy consumed compared with complex algorithms from earlier studies.

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“To my father mercy and forgiveness”

DECLARATION

I hereby declare that the thesis is my original work except for quotations and citations which have been duly acknowledged.

Date: / / 2023 Marwah Adeeb Dhahir

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LIST OF ABBREVIATIONS

Abbreviation	Description
AOA	Angel Of Arrival
BS	Base Station
BP	Basic Pursuit
$BPDN$	Basic Pursuit Denoising
CS	Compressed Sensing
DSN	Directional Sensor Network
$DV-hop$	Distance Vector-hop
EKF	Extended Kalman Filter
$HMDP$	Hierarchical Markov Decision Process
$HMTT$	Hierarchical Multiple Target Tracking
IA	Iterative Activation
$IA-LSCS$	Iterative Activation Leas Squares Compressive Sampling
KF	Kalman Filter
KNN	K-Nearest Neighbor
MDP	Markov Decision Process
MSE	Mean Square Error
$MTLCS$	Multiple Target Localization Compressive Sensing
MTT	Multiple Target Tracking
NSP	Nullspace Property
OMP	Orthogonal Matching Pursuit
PSO	Particle Swarm Optimization
RIP	Restricted Isometry Property
ROC	Receiver Operating Characteristic
$ROMP$	Regularised Orthogonal Matching Pursuit
RSM	Region Segmentation Method
RSP	Range Space Property
RSS	Received Signal Strength
$RSSI$	Received Signal Strength Index
SNR	Signal to Noise Ratio
$TDOA$	Time difference of arrival
TOA	Time Of Arrival
UKF	Unsecented Kalman Filter
$VD-TMTL$	Voronoi Diagram Two-phase Multiple Target Localization
WSN	Wireless Sensor Networks

LIST OF SYMBOLS

Symbol	Definition
Δ	the tolerable quantization error.
Δt	The measurements period.
$\boldsymbol{\phi}$	The random measurement matrix
α	Constant associated with the transmitter and receiver circuits.
β	Constant associated with the transmitter and receiver circuits.
μ	The path loss exponent.
σ_a^2	The random acceleration standard deviation.
$\sigma_{x_m}, \sigma_{y_m}$	The measurement error standard deviation.
$\boldsymbol{A}$	The coefficients matrix.
$\boldsymbol{B}$	The control input matrix.
$\boldsymbol{D}$	The measurement matrix.
D_{max}	The maximum distance that can be sent by the sensor.
E_{TX}^i	The total energy consumed by the i^{th} sensor nodes to send data over a communication channel to the CH.
$\boldsymbol{F}$	The state transition matrix.
$\boldsymbol{H}$	The observation matrix.
$\boldsymbol{I}$	The identity matrix.
K	The number of the nearest neighbor.
$\boldsymbol{K}_{t+1}$	The Kalman Gain.
M	The number of the sensor nodes in the network.
N	The number of the grid points in the network.
$\boldsymbol{P}_{t+1,t}$	The predicted error covariance.
$\boldsymbol{P}_{t,t}$	The error covariance of the current state estimation.
$\boldsymbol{Q}$	The covariance matrix.
$\boldsymbol{R}$	The measurement noise.

LIST OF SYMBOLS

Symbol	Definition
$\boldsymbol{a}$	The target.
$\boldsymbol{b}$	The distance vector.
$\boldsymbol{d}$	The vector collected the measurement distances for all targets.
d_{min}	The minimum distances for which the target can be detected by the sensor.
d_{max}	The maximum distances for which the target can be detected by the sensor.
$d_{i,BS}$	The Euclidean distance between the i^{th} sensor node and the BS.
$d_{i,j}$	The Euclidean distance between i^{th} sensor and j^{th} grid point.
$d_{i,h}$	The Euclidean distance between the i^{th} sensor node and target.
$\boldsymbol{k}$	The recovered target vector.
m	The number of the target detection in the field.
n	The number of data bit.
$s_a = (x_a, y_a)$	The two-dimensional location of the target.
$s_i = (x_i, y_i)$	The two-dimensional location of thei^{th} sensor node.
$s_j = (x_j, y_j)$	The two-dimensional location of thej^{th} grid point.
$\boldsymbol{u_{t-1}}$	The control vector.
$\boldsymbol{v_t}$	The measurement noise vector.
$\boldsymbol{w_{t-1}}$	The process noise vector.
$\boldsymbol{x}$	A signal input
$\boldsymbol{x}_t$	The observation noise vector.
$\widehat{\boldsymbol{x}}_{\boldsymbol{t+1,t}}$	The predicted next state of the target at time step $t + 1$.
$\widehat{\boldsymbol{x}}_{\boldsymbol{t,t}}$	The current state vector.
$(\dot{x}_a, \dot{y}_a)$	The target velocity.
$(\ddot{x}_a, \ddot{y}_a)$	The target acceleration projected.
$\boldsymbol{y}$	The measurement vector
$\boldsymbol{z}_t$	The observation state vector.

CHAPTER 1

GENERAL INTRODUCTION AND LITERATURE REVIEW

1.1 Introduction

Recent important developments in computer networking, microelectronics, and wireless communications have made it possible to create large networks called WSN. WSN is the most widely used and common field of wireless technology [1].

WSN consists of many small sensors node, low-cost devices that serve specific tasks, and a fusion center or BS [2]. The sensor node may be static or mobile, depending on the application requirements [3]. The sensors node are randomly or deterministically deployed in a field of interest [4]. When the environment of interest is inaccessible or located in hostile territory, sensor nodes may be dropped from the aircraft or by other methods, resulting in a random placement [5].

WSNs have attracted the attention of researchers over the last few years due to their wide use in different applications, such as military, civil, intelligent cities, and industry control [6, 7]. One potential application of WSN is remotely monitoring patient physiological data [8]. Furthermore, WSNs have environmental applications like water monitoring, air monitoring, and emergency alerting [9].

Target detection is a vital service of WSN that has security uses in homes to detect infiltration, enemies in battle, and monitor animals' movement [10]. In addition, target detection is considered the first step to locating and tracking a mobile target, The goal of target tracking is to secure the tracks of targets moving over the field of observation continuously with the help of field measurements from sensor nodes. Tracking a mobile target is attractive to some applications and is necessary to continue tracking the detected target over a large area, such as wildfires, toxic gases, oil spills [11], battlefield information monitoring, and traffic management [12].

1.2 Localization Techniques

The majority of localization techniques used in WSN nowadays can be divided into two groups: range-free techniques and range-based techniques [13].

Algorithms in range-free approaches do not require precise knowledge of the angle or distance between the target and sensor nodes. By using connection data or shared multi-hop routing information, range-free algorithms can obtain the distances between the unknown target and sensor nodes inferred indirectly. The binary sensor is used with range-free algorithms, this sensor sends 1 if the target is within its sensing range. Range-free based localization has several benefits, but its main advantages are its low hardware cost and ease of computation. These advantages make them easy to integrate into WSN. Even so, because of their poor location accuracy, their usage is still limited [14].

With range-based positioning systems, the target is located using accurate distance information. Multilateration or Least Squares (LS) can be applied to determine the position when distance estimations are known. Several measurements, including Time Of Arrival (TOA), Time Difference Of Arrival (TDOA), Angle Of Arrival(AOA), and

Received Signal Strengths(RSS), have been suggested in the literature to determine distance [15]. In real-world applications, the TOA and TDOA methods are more precise than the RSS method [16]. TOA-based localization is actually a range-based localization problem. TOA has calculated both ways or round trip. The measured distance between the sensor and the target is obtained by multiplying the computed TOA by a specified propagation speed.

1.3 Problem Statement

1. Multiple target detection and tracking via WSN.

2. Effect of using the practical sensor node in the detection process.

3. A sensor management in multi-target tracking.

4. Limited energy batteries.

1.4 Literature Review

Many researchers have focused on multi-target detection and tracking due to their wide use in different applications. This section presents the literature related to the methods of multi-target detection and tracking. The review starts with target detection, and then target tracking.

1.4.1 Multi-Target Detection

Several localization algorithms have been proposed in the literature for WSN applications which include the compressed sensing (CS) method [17–21], and linear estimation algorithm [22, 23].

1.4.1.1 Compressed Sensing Method

Feng et al. [17] in 2009: The proposed algorithm uses RSS to find the location of targets. They consider k targets which can appear in the isotropic area with unknown locations. The area is divided into discrete N grid points. The M sensors take RSS measurements from the targets to determine the location of these targets accurately, using a small number of RSS measurements. To apply CS theory, appropriate data processing is necessary. Pre-processing was employed to create the incoherence required by the CS theory, while post-processing was used to make up for the spatial discretization brought on by the grid assumption. The simulation results show that the proposed CS method outperforms the kernel method, K Nearest Neighbours, and histogram methods, which use RSS for wireless node localization.

Liu et al. [18] in 2014: In this study, a range-free algorithm (binary sensor) was proposed using the theory of Multiple Target Localization Compressive Sensing (MTLCS). The sensor network monitoring area is divided into many small networks. Msensor nodes with location information are published randomly within some networks. The author assumes that there is at most one node for each grid. K targets are dispersed in different grids, and there is one target per network. Furthermore, the location of the real target is assumed as the corresponding grid center. In this approach, the sensors send the measurements vector and sensing matrix to CH, Which increases the energy consumed by the sensors. Simulation results show that MTLCS has a localization error of less without physical distance measurement. With an increase in targets, the localization error increases. The localization accuracy will increase as the number of sensor nodes increases.

Xin et al. [19] in 2015: In this research, another CS-based approach for multiple target detection. The researcher solves two problems. For the first problem, the authors utilized an iterative activation algorithm (IA) that aims to activate the sensors of better readings with greater probabilities compared to systems that activate all sensors equally. Choosing a section of the sensor schedule allows continuous monitoring of all targets, and saves energy and bandwidth resources. Each activated sensor records the RSS values of the signals received from targets and sends the information to the CH where a compressive sampling algorithm is conducted to recover the number and locations of targets. For the second problem, a sequential recovery algorithm IA-LSCS is proposed, Which exploits all the previous information to improve the accuracy of the localization algorithm. Extensive simulations show that the IA-LSCS algorithms are efficient and the localization accuracy of the IA-LSCS algorithm outperforms DV-hop is a range-free approach and Kernel-based is a range-based approach.

Qian et al. [20] in 2015: The researchers implemented two stages: an offline stage and an online stage for multiple target detection and power estimation in WSN. While this is not the first work on applying compressed sensing (CS) to detection targets, It is the first to achieve localization without prior knowledge of the transmitting powers of targets. At the offline stage, the sensing matrix is generated by collecting RSS from radio frequency emitters, avoiding the drawbacks of the radio propagation model. Then, at the online stage, a small number of RSS measurements are taken to accurately retrieve a sparse vector. The M RF emitters in the offline stage deployed and M sensors in the online stage based on the same deployment scheme, which is simply chosen as random propagation. Their simulation results show that the performance of the proposed approach achieves a high level of positioning and energy estimation accuracy and shows strong performance against measurement noise.

Li et al. [21] in 2020: In this paper, a multiple-target localization algorithm named CS-based two-stage multi-target localization algorithm combined with Voronoi scheme (VD-TMTL) is used. Voronoi Diagram-based Greedy Matching Pursuit method is used to search for candidate networks in local sub-regions. In the fine localization phase, the candidate grids are refined into small grids according to the Least Grid Side Length theory to localize the elements to obtain a higher localization accuracy. Simulations present that the VD-TMTL algorithm has good localization accuracy and at the same time it reduces the response time significantly.

In [17–19, 21], the authors assumed that the number of active sensors is usually a function of the number of targets which is unknown in advance. In [17–19], the authors also supposed that both targets and sensor nodes are located on grid points, which is not a practically valid assumption.

In all the CS-based approaches [17–21], some sensors are selected to perform the sensing task of the targets, which reduces the number of active sensors. However, this sensor selection process requires centralized coordination, which increases the consumed power by the sensors. Furthermore, reducing the number of active sensors does not imply that the lifetime of the WSN increases because there is no reduction in the number of bits per target in the active sensors.

1.4.1.2 Linear Estimation Algorithm

Kang et al. [22] in 2021: The authors presented a hybrid single-target localization algorithm-based multi-target localization scheme that is computationally effective. Based on combinations of measurements in a few chosen anchor nodes, a set of target candidates were estimated, and ghost targets were eliminated using the Mean Square

Error (MSE) criterion. The proposed algorithm grouped the measurement sets in each sensor node with respect to the best M target candidates after obtaining them. The target position was therefore good by using a single-target localization technique, on the clustered measurement sets in every node. Simulation results verify the proposed algorithm's robust performance, which derives the single-target algorithm's performance in the presence of extreme noise. In conclusion, the primary contribution of this work is the development of a computationally effective localization method for a set of multiple targets based on RSS and AOA data that are not associated with the targets from which they were collected.

Luomala and Hakala [23] in 2022: Used a traditional methods to multi-target detection. A multilateration approach is used, which depends on the Time Of Arrival(TOA) measurements for target detection. The sensors in this approach send the information of each target individually. This approach provides a rigorous estimate of target locations, regardless of their number and locations. However, the number of transmission processes for detecting multiple targets can dramatically affect the lifetime of the WSN.

1.4.2 Multi-Target Tracking

Yeow et al. [24] in 2007: In this study, the Hierarchical Multiple Target Tracking (HMTT) distributed target tracking algorithm was used, which can save more energy than other techniques with the same tracking accuracy. The authors employed the Hierarchical Markov Decision Process (HMDP) for the target-tracking (HMTT) algorithm. This algorithm saves energy by determining the optimal sleep time for the sensors, decreasing the rate of sensing (temporal management) while maintaining a respectable tracking accuracy through trajectory prediction (spatial management) of multiple targets. However, HMTT is not accurate, because it is interested in where locations targets are, focused on regions of the target rather than exact Cartesian coordinates. Simulation results showed the effectiveness of HMTT in energy conservation and tracking accuracy.

Fuemmeler and Veeravalli [25] in 2010: Suggest that the sensors be set into sleep mode with a timer that controls the sleep period, to conserve energy. It is expected that a sensor asleep cannot send the information or sense. Therefore, the sensor does not spend energy and remains retained. Based on all the data the sensor has access to, the length of sleep must be decided before the sensor goes to sleep. However, there is a trade-off between energy savings and tracking problems, that come from the sleeping activities at the sensors since having sleeping sensors in the network could cause tracking errors. The results indicate that the design and effectiveness of sleeping regimes that maximize this trade-off are studied, and the data about the object's location can greatly enhance the trade-off between energy use and tracking errors.

Fu et al. [12] in 2012: To balance the tracking performance and costs subject to limited network resources in terms of energy, communication bandwidth, and sensing range, the authors employed decentralized sensor management algorithms to perform sensor selection, where each sensor decides independently whether to participate in data collection and how to contribute to track fusion. The power-saving strategy in this paper is to put some of the sensors into sleep mode using a two-step approach. So that most of the sensors only need to work in the simple sensor module by measuring Signal to Noise Ratio (SNR) while only a small group of properly selected sensors need to perform active sensing by activating their TOA/DOA measurement module. This approach dramatically reduces the energy consumption of the active sensor.

Mohajerzadeh et al. [26] in 2018: In this paper, a reliable method for tracking mobile targets using Directional Sensor Networks (DSNs). Directional sensor networks (DSNs) are a subclass of WSNs with some distinctive advantages. First, the coverage for an incoming detection is achieved by choosing a small subset of borderline sensor nodes. Second, the author suggests an effective method for determining the bare minimum number of interior sensor nodes that should be active, which works for both deterministic ordered and random node deployments. By doing this, the network lifetime can be increased by using a lot fewer sensor nodes. Third, used an engineering method to collect data with two active sensors simultaneously. Finally, the target location is estimated using an extended Kalman filter (EKF). The results show the effectiveness of the proposed scheme in terms of energy efficiency, coverage, and tracking accuracy.

Parvin and Vasanthanayaki [27] in 2019: In this research work, a distributed energy optimization method for target tracking is implemented using Particle Swarm Optimization. Effective target tracking based on speed, acceleration, and angle of movement is performed by selecting the shortest energy-saving path. The proposed system depends on the best path selection leads to better performance. From the simulation, it can be seen that the proposed system indicates slightly better results than the previous systems.

Zou et al. [28] in 2022: Propose a new resource allocation scheme for performing accurate node scheduling and accurate tracking in networks for mobile multi-target tracking. The dynamic tracking problem has been formulated as an infinite horizon Markov Decision Process (MDP), taking into account the variety of different target nodes and the various tracking capabilities of different sensor nodes. Moreover, the multi-region tracking and scheduling strategy is treated as an important component in reducing the size of the state space with low computational complexity. The proposed system can obviously enhance network performance and reduce tracking delay as shown by simulation experiments. Moreover, sink nodes can reduce regular energy consumption through scheduling policy. Finally, the time complexity is analyzed to promote more work smoothly.

Lee et al. [29] in 2023: This study combines the Received Signal Strength Index (RSSI) channel model with the Particle Swarm Optimization (PSO) technique to locate and track indoor targets. For target localization and tracking, the effectiveness of eight different method combinations with random or regular points, fixed or adaptive weights, and the Region Segmentation Method (RSM) proposed in this paper is examined for the number of particles in the PSO algorithm with 12, 24, 52, 72, and 100. The simulation results show that the employment of more algorithms improves the accuracy and stability of target location estimate, but increases target location estimation time. As a result, this study presents the RSM. The simulation results suggest that the proposed RSM approach may increase positioning and tracking speed while reducing the number of particles employed in the PSO algorithm, all without compromising target localization and tracking accuracy.

1.5 Objectives

The main contributions of this work can be stated as follows.

1. Presents a reliable target detection and tracking technique based on the CS theory using the TOA measurements. The proposed approach can detect and track multiple targets simultaneously.

2. Suggests centralized sensor node management algorithm.

3. Extend the lifetime of the sensors inside the network.

1.6 Organization of Thesis

- **Chapter two:** This chapter provides a brief description of WSN in terms of network models and mathematical models as well as background information on the algorithms used in the work. Those techniques include a multilateration approach, Compressed Sensing theory (CS), K- Nearest Neighbors algorithm (KNN), and Kalman Filter (KF).

- **Chapter three:** It covers the proposed model for multi-target detection, the practical approach for the proposed model, the energy model, sensor management, and multi-target tracking.

- **Chapter four:**It covers simulation results for multi-target detection and tracking to compare the results of the proposed model (CS) with the traditional approach (multilateration) illustrated in Chapter Two.

- **Chapter five:** This chapter presents the proposed model's summary conclusions and offers suggestions for future work.

CHAPTER 2

THEORETICAL BACKGROUND

This chapter presents an overview of WSN, in addition to the required background information on the algorithms used in the work. Those techniques include a multilateration approach, Compressed Sensing theory (CS), K- Nearest Neighbors algorithm (KNN), and Kalman Filter (KF).

2.1 Overview of WSN

WSNs are formed of a vast number of cheap, tiny active sensor nodes that are typically dispersed at random in a two-dimensional field [30]. Each sensor node is able to sense, process, and send data to the BS.

Target detection and tracking is a crucial WSN service with security applications such as identifying intruders, enemies in battle, and tracking the movement of animals [31]. The target tracking objective is to continually secure the tracks of targets moving over the field of sight using field measurements from sensor nodes. Target detection is also regarded as the first step in detecting and tracking a mobile target. Certain applications, such as those for monitoring wildfires, hazardous gases, oil spills, and traffic management need tracking a movable target in order to continue tracking the identified target across a vast area [11].

Based on the working principle of the sensor, they are classified into the following categories: active and passive sensors. An active sensor generates the signals and emitted them to the monitoring field, and then receives the signal that is emitted after reflecting from the target. The passive sensor measures the strength of the signal emitted by the physical target. Different from the active sensors, the passive does not generate the signals [32].

The sensor consists of a processor, a sensing device, and a radio or communication unit that is used to send information collected by the sensors to a central unit called the BS [33]. BS processes the data received from the sensors in the network before handing them over to the receiver. BS has the higher processing power and energy than all other sensors in its service area [34].

Power is a compulsory aspect of nearly all operations at WSN. In general, the power consumption of sensor nodes is noted in three places: (a) power consumption by the sensing unit, (b) power consumption by the processing unit, and (c) power consumption by the communication unit [5]. The power consumption in sending data (communication unit) is higher than in sensing and computation. It is observed that 80% of the sensor node's power is consumed by the communication unit [35]. The energy consumed by i^{th} sensor node E_{TX}^{i} for transmitting a packet of $n - bit$ of data over a communication channel to the BS can be described using the free-space energy model as follows [34, 36]:

$$E_{TX}^{i} = (\alpha + \beta \times d_{i,BS}^{\mu}) \times n \tag{2.1}$$

where α and β are constants related to the transmission and reception circuity, $d_{i,BS}$ is the distance between the i^{th} sensor and BS, $\mu \in (2, 6)$ is the free-space exponent [36].

The sensors are limited energy devices. The batteries inside sensor nodes are difficult to replace or recharge due to the harsh environment in which sensors are usually deployed [37]. When any sensor consumes its battery resources (i.e., dies out), it leads to a gap in the network, and therefore the WSN cannot detect and track all targets appearing in the monitoring field. One criterion used to measure the energy efficiency of WSNs is the lifetime. The lifetime of the WSN is defined as the number of rounds the sensors send information to a fusion center until the first sensor dies [34, 38].

Typical measurements for target detection include the TOA, TDOA, AOA, and RSS [15]. TOA and TDOA methods are more accurate than the RSS method in practice [16]. Moreover, RSS/AOA measurements are calculated based on the signal that the targets generate, the RSS/AOA measurements cannot be determined by their original targets in non-cooperative situations such as military applications. TOA is utilized to target detection, where all active sensors emit a signal with the same power in the monitoring field, and measure the two-way travel time to detect the presence and number of targets. TOA-based localization techniques treat the location-finding problem as a distance estimation problem based on the reflected signal from the targets.

For Multiple Target Tracking (MTT), due to the narrow bandwidth, limitation energy, and sensing range constraint of the sensor nodes, it is impossible to track the moving target by the same subset of static sensors [12]. Also, it is not helpful to use all the sensors in the tracking, since the sensor that is far away from the targets consumes power, and its measurement is inaccurate. From the points mentioned above, the sensor management problem appeared, which aims to assign the sensors that surround the targets (nearest neighbor) to carry out the tracking process for a moving target [12].

The three common divisions of target tracking are target detection, target localization, and prediction of the targets' trajectories [39].

2.2 Multilateration Approach

When monitoring the field of dimensions ($R \times R$). The targets can appear at any location in the monitoring field. The BS is located in the center of the monitoring field. The static sensors node is distributed randomly in the monitoring field. The locations of sensor nodes are known and obtained via GPS or by using self-localization algorithms [40]. Assume that the sensors are $i = 1, 2, \ldots, M$, where $s_i = (x_i, y_i)$ is the coordinates of the sensor's node location. When a sensor node senses the relative distances between itself and the targets inside the monitoring field. Given the distances and locations of sensor nodes, the target can be localized and detected. In the traditional approach [23], the authors utilized a multilateration approach for target detection. It is an approach to determining locations that are widely used in WSNs. When m targets appear simultaneously in the monitoring field, each sensor node measures its relative distances to all of the m targets with unknown location (x_a, y_a) by using TOA and reports this information to the BS. In this approach, the sensors send the information of each target individually [23]:

$$\begin{bmatrix} \boldsymbol{d}_1^2 \\ \boldsymbol{d}_2^2 \\ \vdots \\ \boldsymbol{d}_M^2 \end{bmatrix} = \begin{bmatrix} (x_1 - x_a)^2 + (y_1 - y_a)^2 \\ (x_2 - x_a)^2 + (y_1 - y_a)^2 \\ \vdots \\ (x_M - x_a)^2 + (y_M - y_a)^2 \end{bmatrix} \tag{2.2}$$

To determine the target's location in BS, the nonlinear distance equation is converted to a linear system. The following system of linear equations is created when the terms are rearranged [23]:

$$\boldsymbol{Ax} = \boldsymbol{b} \tag{2.3}$$

where $\boldsymbol{A} \in R^{M-1}$ is the coefficients matrix (It is calculated using sensors coordinates) and can be defined as follows:

$$\boldsymbol{A} = \begin{bmatrix} 2(x_M - x_1) & 2(y_M - y_1) \\ 2(x_M - x_2) & 2(y_M - y_2) \\ \vdots & \vdots \\ 2(x_M - x_{M-1}) & 2(y_M - y_{M-1}) \end{bmatrix} \tag{2.4}$$

,

and the distance vector $\boldsymbol{b} \in R^{M-1}$ is expressed as follows:

$$\boldsymbol{b} = \begin{bmatrix} d_1^2 - d_M^2 - x_1^2 - y_1^2 + x_M^2 + y_M^2 \\ d_2^2 - d_M^2 - x_2^2 - y_2^2 + x_M^2 + y_M^2 \\ \vdots \\ d_{M-1}^2 - d_M^2 - x_{M-1}^2 - y_{M-1}^2 + x_M^2 + y_M^2 \end{bmatrix} \tag{2.5}$$

The final two-dimensional location of the target is estimated as follows:

$$\boldsymbol{x} = (\boldsymbol{A^T A})^{-\boldsymbol{1}} \boldsymbol{A^T b} \tag{2.6}$$

The above approach is repeated for each target.

The multilateration approach provides a rigorous estimate of target locations, regardless of their number and locations. However, the amount of data transmission for detecting multiple targets can dramatically affect the lifetime of the WSN, which is considered one of the main issues in WSN. In the following subsection, we propose an approach that can extend the lifetime of WSN, without affecting detection quality. The proposed approach depends heavily on CS theory.

2.3 Compressed Sensing (CS) Theory

CS has gained the attention of researchers in recent years and has been employed in many fields such as image processing, array processing, military target detection, Multiple-Input Multiple-Output (MIMO) radar systems for target detection and direction of arrival estimation, and medical imaging [41–43]. Just lately, the CS theory has been applied to target detection using specific data. CS can reconstruct a sparse signal using a small number of samples as compared to Nyquist sampling under specific conditions like Mutual Coherence, Restricted Isometry Property (RIP), Nullspace Property (NSP), and Range Space Property (RSP) [44, 45]. CS is applied to reduce the data volume that needs processing, which leads to lower energy consumption in WSN and faster data processing [46].

The CS works by using fewer random measurements. Then the CS problem can be formulated as shown in Figure 2.1 as follows:

$$\boldsymbol{y} = \boldsymbol{\Phi}\boldsymbol{x} \tag{2.7}$$

where $\boldsymbol{x} \in R^N$ is a signal input. $\boldsymbol{\Phi} \in R^{M\times N}$ is random measurement matrix and $\boldsymbol{y} \in R^M$ is the measurement vector. Compressive measurements are produced by multiplying the input signal by the random measurement matrix. The length of the input

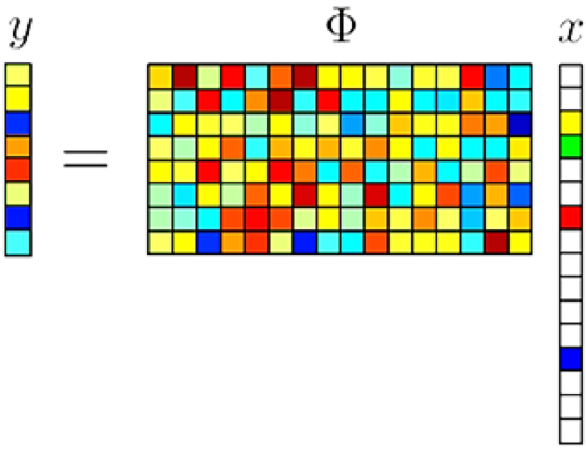


Figure 2.1: CS Model.
[47]

signal is longer than the number of measurements ($M << N$). The sparsity of the input signal has a direct relationship with the size of the measurement matrix and, thus, the total number of measurements. The measurement matrix must be incoherent with the basis where the signal is represented sparsely in order to further reduce the number of measurements needed for accurate reconstruction [48, 49].

Recover $\boldsymbol{x}$ from knowledge of by measurement vector $\boldsymbol{y}$ and measurement matrix $\boldsymbol{\Phi}$ is utilized in the CS reconstruction algorithm. When data is compressed, a set of undetermined equations must be solved in order to reconstruct the data. There are an infinite number of ways to reconstruct x, and discovering the perfect candidate involves limited minimization of the $\ell_g(\boldsymbol{x})$ norm [50]:

$$argmin\|\boldsymbol{x}\|_g \quad s.t. \quad \boldsymbol{y} = \boldsymbol{\Phi x} \tag{2.8}$$

The optimal solution would be ℓ_0, but since finding all nonzero elements is all it takes to obtain the answer, it is excessively noise-sensitive (easily satisfied by noise). Basic Pursuit (BP), which employs global optimization and is capable of stable super-resolve

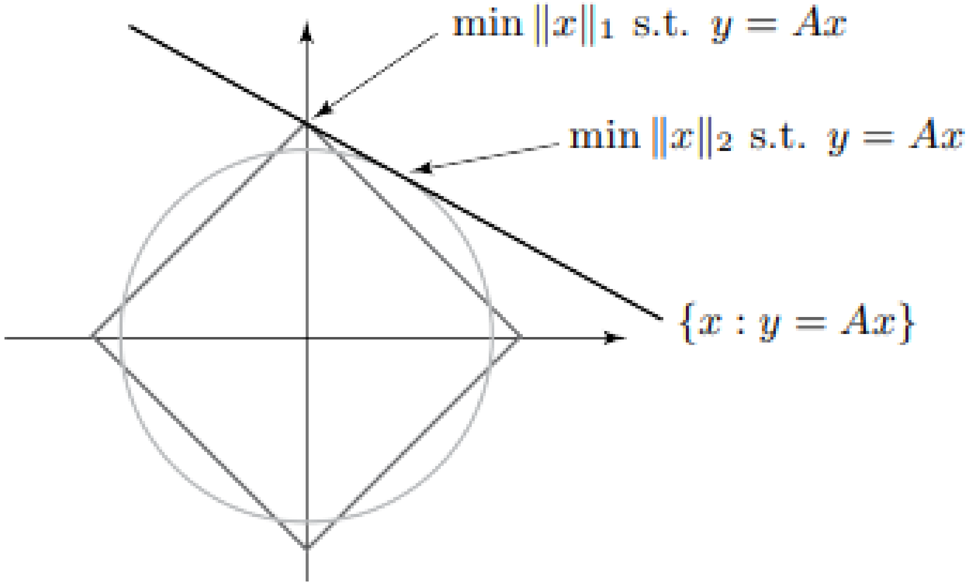


Figure 2.2: ℓ_1 minimization versus ℓ_2 minimization
[52]

for the ℓ_1 norm [51]. Due to the ℓ_1 ball's form, ℓ_1 minimization does in effect enhance sparsity. To illustrate this fact, we refer the reader to Figure 2.2, in which the ℓ_1 minimization is compared to ℓ_2 minimization.

Additional recovery methods include Orthogonal Matching Pursuit (OMP) [53], Basis pursuit Denoising (BPD) [54], and Regularised OMP (ROMP) [55]. BP is the most commonly employed linear programming approach when compared to other approaches [56].

2.4 K-Nearest Neighbor

KNN is a simple but effective machine learning algorithm [57]. It is one of the oldest algorithms and simplest ways to classify patterns. It is applied to classify data based on the nearby of a particular query point. Its performance depends critically on the distance measurement used to locate nearest neighbors [58]. The value of K in the KNN algorithm determines the number of neighbors scanned to determine the classification of a given query point.

The KNN has been employed in many different applications like data prepossessing, finance, medical diagnosis, prediction, and pattern recognition [59]. The KNN can be implemented in different applications for WSN such as intrusion detection [60], missing data estimation [61], a query that facilitates the collection of sensor data samples [62], location estimation [63].

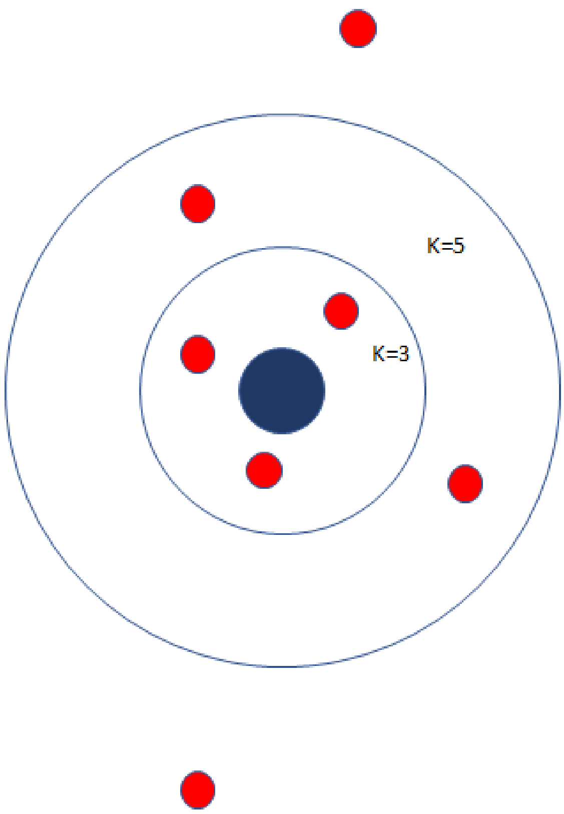


Figure 2.3: A simple KNN

The unlabeled data is categorized using the nearest neighbor technique by figuring out which class its neighbors fall within. This idea is utilized in the calculation of the KNN algorithm [64]. With the KNN algorithm, a particular value of K is fixed, assisting us in categorizing the unknown tuple [65]. Figure 2.3 shows the sample example for KNN. The Euclidean distance and K's value are two variables that determine KNN performance. The steps are as follows in order to understand the algorithm's operation:

Given the data set: $(x_1, y_1), (x_2, y_2), \ldots (x_N, y_N)$

Step 1:store the data set (red circles).

Step 2: calculate the Euclidean distance between a particular query point (x, y) (blue circle) and each data set using the formula:

$$\sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{2.9}$$

Step 3: Find the KNN by choosing the data that is nearest to the particular query point.

The classification's outcome is sensitive to the value of K. The input value K determines how many neighbors must be taken into consideration. From Figure 2.3 if $K = 3$ then the nearest neighbor became 3, and when $K = 5$ the nearest neighbor became 5.

2.5 Kalman Filter

The KF algorithm uses a linear method for estimating the optimal state. A KF acts as a filter and the objective of the filter is to take a series of measurements observed over time containing uncertainty, noise, or some errors to predict the next state certainty [66]. KF is adapted in many application fields such as guidance, navigation, and control of vehicles and aircraft. Furthermore, it also plays an important role in the fields of spacecraft orbit calculations, ship positioning, sensor data fusion, and digital image processing [67]. In addition to tracking the moving targets [68]. KF has an easy-to-understand structure and needs little processing power. Also, it is attractive that theoretically. The ideal state is precisely determined with the minimum variance error [68].

2.5.1 Problem Definitions

In state space format, KF is exploited to estimate states based on linear dynamical systems. The process model gives the following description of the state's evolution from time $t-1$ to time t [69]:

$$\boldsymbol{x}_t = \boldsymbol{F}\boldsymbol{x}_{t-1} + \boldsymbol{B}\boldsymbol{u}_{t-1} + \boldsymbol{w}_{t-1} \tag{2.10}$$

Where $\boldsymbol{F}$ is the state transition matrix used to apply to the prior state vector $\boldsymbol{x}_{t-1}$, $\boldsymbol{B}$ is the control-input matrix used to transform the control vector $\boldsymbol{u}_{t-1}$, and $\boldsymbol{w}_{t-1}$ is the process noise vector, which is defined as being zero-mean Gaussian with the covariance $\boldsymbol{Q}$, i.e., $\boldsymbol{w}_{t-1} \sim \mathcal{N}(0, \boldsymbol{Q})$.

The measurement model is operated in concert with the process model to describe the relationship between the measurement and the state at the current time step t as [69]:

$$\boldsymbol{z} = \boldsymbol{H}\boldsymbol{x}_t + \boldsymbol{v}_t \tag{2.11}$$

where $\boldsymbol{z}$ is the measurement vector, $\boldsymbol{H}$ is the measurement matrix, and $\boldsymbol{v}_t$ is the measurement noise vector that is assumed to be zero-mean Gaussian with the covariance $\boldsymbol{R}$, i.e., $\boldsymbol{v}_t \sim \mathcal{N}(0, \boldsymbol{R})$. Note that sometimes the term 'measurement' is called 'observation' in different literature.

The role of the KF is to provide an estimate of $\boldsymbol{x}_t$ at time t, given the initial estimate of $\boldsymbol{x}_0$, the series of observations, $\boldsymbol{z}_1, \boldsymbol{z}_2, \ldots, \boldsymbol{z}_t$, and the details of the system as represented by $\boldsymbol{F}, \boldsymbol{B}, \boldsymbol{H}, \boldsymbol{Q}$, and $\boldsymbol{R}$. Note that by assuming that they are invariant across time, as in most applications, subscripts to these matrices are omitted here. The covariance matrices are intended to reflect the statistics of the noise. However, in many practical applications, the true statistics of the noises are unknown or not Gaussian. In order to achieve a desired performance, $\boldsymbol{Q}$ and $\boldsymbol{R}$ are typically employed as tuning parameters that the user can change [70].

CHAPTER 3

THE SIMULATION MODEL DESCRIPTION AND METHODOLOGY

3.1 Introduction

This chapter involves explains the mathematical models of multi-target detection and tracking by using CS theory, practical scenarios, energy model, sensor management, and KF.

=

3.2 Proposed Target Detection Approach

Compressed sensing (CS) theory formulates the multiple target detection problem as approximating a sparse vector with some TOA measurements. The sensors collect the signals reflected off all targets, and send them in one packet to the BS [71]. The approach reduces the number of transmission processes of the target detection in the monitoring field, which reduces the energy consumption in the transmission process, and detection time, and increases the lifetime of WSN by reducing the number of bits for all targets. The CS approach also does not put constraints on the location of the sensor nodes (i.e., off-grid sensors).

Suppose that we have a field of dimensions ($R \times R$). The field is partitioned into N uniformly-spaced grid points. Assume that the grid points are $j = 1, 2, \ldots, N$, where $s_j = (x_j, y_j)$ is the coordinates of the location of the grid points. The m on-grid targets appear inside the monitoring field. Also, there is a single BS that is located in the center of the monitoring field. Static sensors are distributed randomly in the monitoring field. The sensors work in two modes: sleep and wake-up. The sensors stay in the sleep state and periodically wake up for a short time to emit a signal with the same power to monitor the field for the existence of targets. The locations of sensor nodes are known and can be obtained via GPS or by using self-localization algorithms [40]. Assume that the sensors are $i = 1, 2, \ldots, M$, where $s_i = (x_i, y_i)$ is the coordinates of the sensor's location. We assume that the number of grid points is greater than the number of sensor nodes ($N >> M$). When a sensor wakes up and m targets appear simultaneously in the monitoring field, each sensor measures its relative distances to all of the m targets by using TOA and reports this information, in one pack to the BS. For each sensor node, the measurement distances are fused in vector $\boldsymbol{d} \in R^{M \times 1}$ and sent to the BS as follows:

$$d_i = \sum_{h=1,\ldots,m} d_{i,h}, \qquad i = 1, 2, \ldots, M \tag{3.1}$$

where m represents the number of on-gird targets.

The BS constructs the measurement matrix $\boldsymbol{D} \in R^{M \times N}$. Each element in this matrix is calculated by using the coordinates of the sensor nodes and grid points as follows,

$$\boldsymbol{D} = \begin{bmatrix} d_{11} & \ldots & d_{1N} \\ \vdots & \ddots & \vdots \\ d_{M1} & \ldots & d_{MN} \end{bmatrix} \tag{3.2}$$

where $d_{i,j}$ represents the distance between sensor i^{th} and grid point j^{th}.

The BS recovered the target vector $\boldsymbol{k} \in R^{N \times 1}$. Assuming that the number of targets inside the scene of interest is small, CS theory can be used to estimate the number and locations of the targets. The problem is to estimate target locations based on the TOA information from all sensors $\boldsymbol{d}$ and the measurement matrix $\boldsymbol{D}$. The problem can be described as follows:

$$\boldsymbol{d} = \boldsymbol{D}\boldsymbol{k} \tag{3.3}$$

Given the sparsity constraints, Basis Pursuit is used to recover the target vector $\boldsymbol{k}$ by solving the following ℓ_1-norm problem:

$$\text{minimize} \quad \|\boldsymbol{k}\|_1 \quad \text{subject to} \quad \boldsymbol{d} = \boldsymbol{D}\boldsymbol{k} \tag{3.4}$$

Where the nonzero elements of the target vector represent the potential presence of a target on the corresponding grid point. In addition, the number of nonzero elements represents the number of detected targets. Thus, our proposed approach can detect the number of targets and their location simultaneously.

3.3 Practical Approach for proposed model

In practice, there are minimum and maximum distance constraints for all the sensors. In this section, we rewrite our model to take into consideration these constraints. Let d_{min} and d_{max} represent the minimum and maximum distances for which the target can be detected by the sensor, respectively. For a specific sensor, TOA readings are reported for targets within the detection range, and targets outside this range are not detected. BS only takes into consideration the sensors that report their reading (i.e., if the target lies between d_{min} and d_{max}) and uses those readings to estimate target locations. Mathematically, this affects some elements in the measurements matrix $\boldsymbol{D}$ to become zeros (out of sensor detection range). This leads to the void of some elements in $\boldsymbol{D}$, which does not affect the size of $\boldsymbol{D}$, nor changes the optimization problem used to localize targets.

3.4 Energy Model

Increasing the lifetime of WSNs is considered one of the most crucial challenges in WSNs. The transmission process to BS consumes most of the sensor energies. During the process of transmission, the data are first converted to a digital form via the quantization process. In this section, we discuss how the data fusion that is described in Eq.(3.1) reduces the number of bits required for transmission. The consumed energy required to transmit the data is modeled as follows [34, 36]:

$$E_{TX}^{i} = (\alpha + \beta \times d_{i,BS}^{\mu}) \times n \tag{3.5}$$

where α and β are constants related to the transmission and reception circuity, $d_{i,BS}$ is the distance between the i^{th} sensor and BS, $\mu \in (2, 6)$ is the free-space exponent [36], and n represents the number of transmitted bits.

In [23], the multilateration approach is used for targets' detection. In this approach, the sensors send the information bits for each target individually to the BS. The number of bits n that are used to transmit all targets' relative distances to BS can be determined as follows:

$$n = m \log_2 \frac{D_{max}}{\Delta} \tag{3.6}$$

where D_{max} is the sensing range (maximum expected distance between targets and sensor nodes), m is the number of targets, and Δ is the tolerable quantization error. Assuming uniform quantization, and from Eq.(3.6), the number of bits is linearly proportional to the number of targets detected inside the field, and the energy required to transmit targets' data is:

$$E_{TX}^{i} = (\alpha + \beta \times d_{i,BS}^{\mu}) \times (m \log_2 \frac{D_{max}}{\Delta}) \tag{3.7}$$

In the proposed CS-based approach, the sensors send their relative distances for all detected targets in one pack to the BS, which reduces the amount of data (the number of bits) sent by a sensor node. The number of bits sent to BS in the proposed approach for achieving an equivalent quantization error as in the multilateration approach is

$$n = \log_2 \frac{mD_{max}}{\Delta} \tag{3.8}$$

and the required energy for transmitting targets' data to BS is

$$E_{TX}^{i} = (\alpha + \beta \times d_{i,BS}^{\mu}) \times (\log_2 \frac{mD_{max}}{\Delta}) \tag{3.9}$$

In the proposed approach, the number of bits is logarithmically proportional to the number of detected targets. One can see that the number of bits required for the proposed approach to multi-target detection is less than that for the multilateration approach.

3.5 Sensor Management

Tracking the moving target with the same subset of static sensors is not practicable due to bandwidth limitations, energy limitations, and the restricted sensing range of the sensor nodes. Moreover, using every sensor on the field is ineffective since sensors located far from the target require more energy and provide inaccurate readings. The sensors closest to the targets (also known as nearest neighbors) are chosen for tracking in order to address this issue.

In each tracking step, the KNN algorithm can be used for sensor management in tracking the moving targets in WSN to select a subset of the sensors based on the target's location. The sensor around the targets is dynamically configured by adding or removing sensors as the target moves through the sensing field. Including KNN not only improves the tracking efficiency but also reduces the search area for the sensors to be activated for future predictions. In each step of tracking the subset of the sensor collected the information of targets using the CS theory and multilateration technique.

3.6 Multi Target Tracking

Target tracking begins after the detection and localization of the target in the field. For target tracking, different linear and nonlinear filters were proposed, such as KF, Extended Kalman Filter (EKF), and Unscented Kalman Filter (UKF).

A KF is a prediction-based algorithm that uses distance as a parameter for estimating the target trajectory. When the targets appear in the field, the sensor surrounding the targets can be estimated the target position $s_a = (x_a, y_a)$ by using CS theory or multilateration technique through the measurement of TOA. The KF works in a two-step process: prediction (time measurements) and update (measurement corrections). The current state vector is employed for computing the predicted system state vector.

State prediction equation [39]:

$$\widehat{\boldsymbol{x}}_{\boldsymbol{t+1,t}} = \boldsymbol{F}\widehat{\boldsymbol{x}}_{\boldsymbol{t,t}} \tag{3.10}$$

Error covariance prediction equation [39]:

$$\boldsymbol{P}_{t+1,t} = \boldsymbol{F}\boldsymbol{P}_{t,t}\boldsymbol{F}^T + \boldsymbol{Q} \tag{3.11}$$

where $\widehat{\boldsymbol{x}}_{\boldsymbol{t+1,t}}$ is the predicted next state of the target at time step $t + 1$, $\boldsymbol{F}$ is the state transition matrix, $\widehat{\boldsymbol{x}}_{\boldsymbol{t,t}}$ is the current state vector, $\boldsymbol{P}_{t+1,t}$ is the predicted error covariance, $\boldsymbol{P}_{t,t}$ is the error covariance of the current state estimation, and $\boldsymbol{Q}$ is the covariance matrix.

Kalman gain equation [39]:

$$\boldsymbol{K}_{t+1} = \boldsymbol{P}_{t+1,t}\boldsymbol{H}^T(\boldsymbol{H}\boldsymbol{P}_{t+1,t}\boldsymbol{H}^T + \boldsymbol{R})^{-1} \tag{3.12}$$

where $\boldsymbol{K}_{t+1}$ is the Kalman Gain, and $\boldsymbol{R}$ is the measurement noise, and $\boldsymbol{H}$ is the observation matrix simplified to:

$$\boldsymbol{H} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}.$$

Estimation update equation [39]:

$$\widehat{\boldsymbol{x}}_{\boldsymbol{t,t}} = \widehat{\boldsymbol{x}}_{\boldsymbol{t+1,t}} + \boldsymbol{K}_{t+1}(\boldsymbol{z_t} - \boldsymbol{H}\widehat{x}_{t+1,t}) \tag{3.13}$$

where $\boldsymbol{z_t}$ is the observation state vector, which represents the coordinates of the targets estimated from the readings of selected sensors surrounding the targets via CS or multilateration technique.

Error covariance update [72]:

$$\boldsymbol{P}_{t,t} = (\boldsymbol{I} - \boldsymbol{K}_{t+1}\boldsymbol{H})\boldsymbol{P}_{t+1,t}(\boldsymbol{I} - \boldsymbol{K}_{t+1}\boldsymbol{H})^T + \boldsymbol{K}_{t+1}\boldsymbol{R}\boldsymbol{K}_{t+1}^T \tag{3.14}$$

where $\boldsymbol{I}$ is an identity matrix.

All KF equations are repeated at every tracking step, with new prediction and covariance matrix.

Algorithm of Proposed Multi-Target Tracking

1. for $i = 1 : S$
2. The BS used KF to predict the location of the target.
3. KNN used the predicted target location to select and activate the subset sensor node around the target.
4. Active sensor node calculated the distance between them and the targets, fusion the information for all targets, and sends them in one pack to BS.
5. The BS received the information and updated the predicted target location. end

CHAPTER 4

SIMULATION AND RESULTS

4.1 Introduction

The results obtained are presented and discussed for two cases (detection and tracking) using the Matlab program. The first case presents Simulation and Results for multi-target detection to compare the results of the proposed model (CS) with the traditional approach (multilateration) illustrated in Chapter Two in terms of the Performance of target detection and network lifetime. The second case presents simulation results for multi-target tracking to compare the results of the proposed model with the traditional approach for MTT in WSN to show the efficacy of tracking and energy efficiency with the CS approach.

4.2 Simulation and Results for multi-target detection

In this section, simulation and results for multi-target detection and the lifetime for WSN are reported. We consider a two-dimensional monitoring field with $100 \times 100\ m^2$. For the CS theory (proposed approach), the field of interest is partitioned uniformly into 100 grid points. A Monte Carlo simulation with 1000 trials was conducted. In each trial, 50 static sensor nodes were distributed randomly, and m targets were randomly placed on the grid points. Figure 4.1 shows the example of WSN with dimension $100 \times 100\ m^2$, 50 sensors were distributed randomly, and a single BS was in the center of the fields.

The $d_{min} = 10\ m$ and $d_{max} = 100\ m$ for the practical approach.

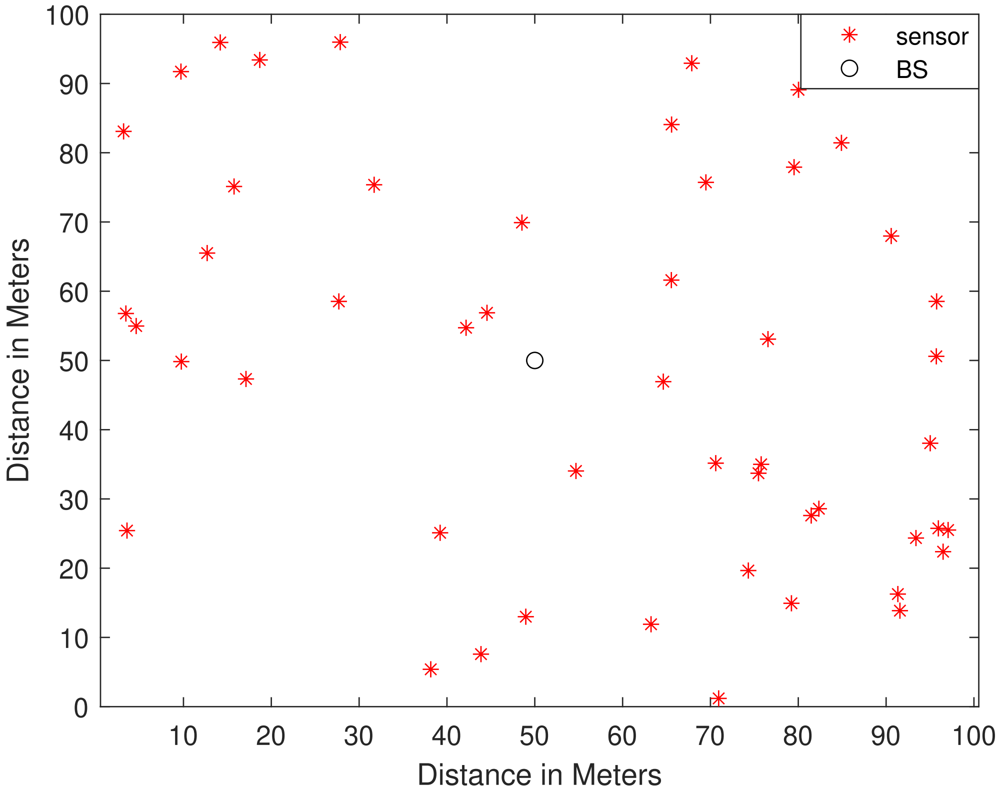
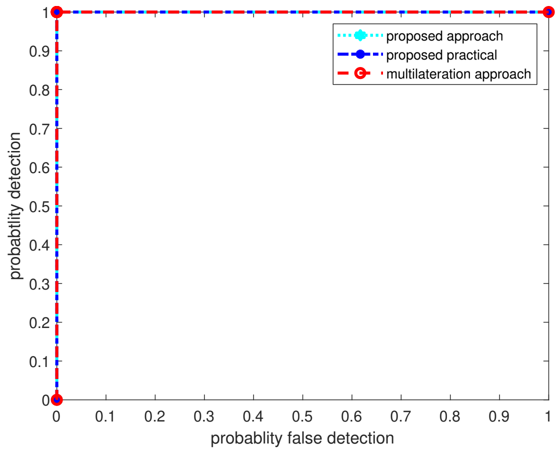


Figure 4.1: An example showing WSN .

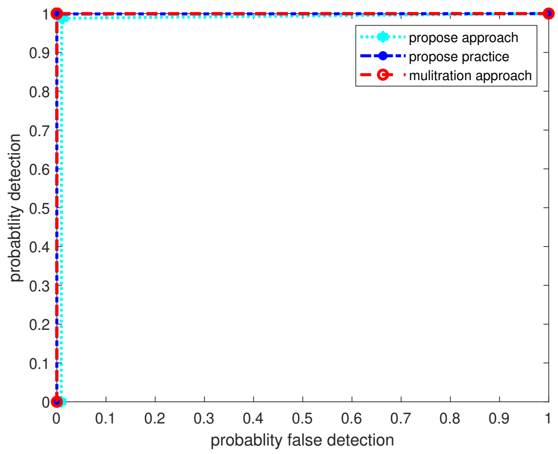
4.2.1 Performance of Target Detection

This subsection presents simulation results regarding target detection among all approaches. The targets were localized using a multilateration approach, CS-based approach, and practical scenarios (section 3.3). Due to the superior performance of the multilateration approach and dependence on TOA to detect the targets, we took this approach as a benchmark to compare with the proposed CS-based approaches. The Receiver Operating Characteristic (ROC) curve is applied to evaluate the performance of all approaches. We declare successful detection when all targets are detected and localized in their nearest grid points. We consider false detection when at least one target that does not belong to the real simulated targets is detected.

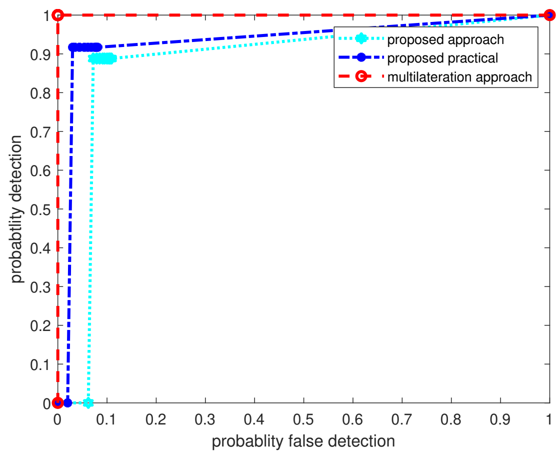
Figure 4.2 shows ROC curves when the number of targets is 6, 12, and 18, respectively. From Figure 4.2(a), one can see that the three approaches detect all targets with the same detection accuracy for 6 targets. On the other hand in Figure 4.2(b), the performance of the CS-based approaches degrades when the number of targets is 12 due to the reduction in the sparsity level. It is worth mentioning that the practical proposed approach performs better than the ideal case for 18 sources as shown in Figure 4.2(c). Such improvement is due to the zeros that appear in the measurement matrix for the practical case, which reduces the correlation among the columns in the sensing matrix $\mathbf{D}$.



(a) detection 6 targets



(b) detection 12 targets



(c) detection 18 targets

Figure 4.2: comparison of the performance of the proposed approach, proposed practical, with the multilateration approach.

4.2.2 Sensors Lifetime in WSN

In this subsection, we compare the lifetime of WSN (i.e., the number of rounds) versus the number of targets for two approaches (proposed and multilateration approaches). The initial energy for each sensor is $1J$. We set D_{max} ,Δ, α, β, and μ to $150m$, $0.15m$, $50nJ/bit$, $100PJ/(bit.m^2)$, and 2, respectively [34, 36]. Figure 4.3 shows the lifetime of WSN for the proposed (CS theory) and the multilateration approaches for a different number of targets. One can see that the proposed approach dramatically increases the lifetime, and the improvement increases as the number of targets increases. This behavior is a result of the fusion process (in Eq. 3.1) which reduces the total number of transmitted bits from the sensors to the BS, as illustrated in Section 3.4.

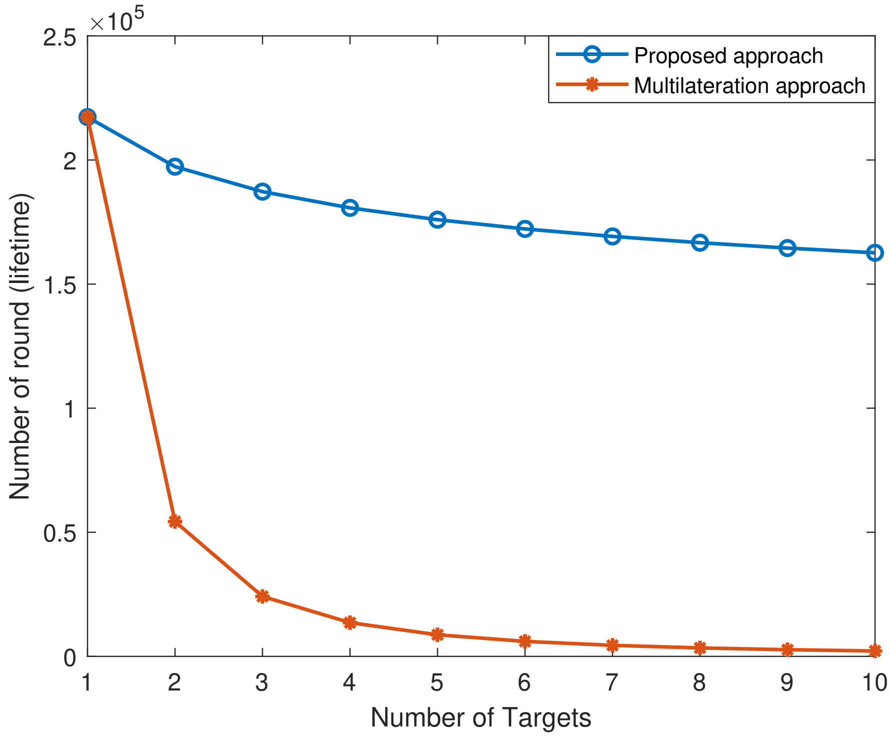


Figure 4.3: Comparison of the lifetime of WSN using the proposed approach, and multilateration approach.

4.3 Simulation and Result for Multi-Target Tracking

This section presents simulation and results for MTT in WSN using a KF to show the efficacy of tracking and energy efficiency with the CS approach. We consider a scene with 100 static sensors node randomly distributed with a radio range of $100\ m$. The sensing field is a $400 \times 400\ m^2$. For the CS theory, the field of interest is partitioned uniformly into $40,000$ grid points. There are $(3, 4)$ moving targets with variable velocity and constant acceleration in the field, and the K of KNN are 10 sensors that surround the targets.

The state vector of target a is defined as $\boldsymbol{x_{t,t}} = \begin{bmatrix} x_a, y_a, \dot{x}_a, \dot{y}_a, \ddot{x}_a, \ddot{y}_{a)} \end{bmatrix}^T$, where (x_a, y_a) is position of the target, $(\dot{x}_a, \dot{y}_a)$ are the target velocity, and $(\ddot{x}_a, \ddot{y}_a)$ are the target acceleration projected onto the x and y coordinates, respectively. We set the initial velocity and acceleration to 0. The equations of target tracking in section 3.6, with parameters given by

$$\boldsymbol{F} = \begin{bmatrix} 1 & \Delta t & 0.5\Delta t^2 & 0 & 0 & 0 \\ 0 & 1 & \Delta t & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & \Delta t & 0.5\Delta t^2 \\ 0 & 0 & 0 & 0 & 1 & \Delta t \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$
\boldsymbol{Q} = \begin{bmatrix} \frac{\Delta t^4}{4} & \frac{\Delta t^3}{2} & \frac{\Delta t^2}{2} & 0 & 0 & 0 \\ \frac{\Delta t^3}{2} & \Delta t^2 & \Delta t & 0 & 0 & 0 \\ \frac{\Delta t^2}{2} & \Delta t & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{\Delta t^4}{4} & \frac{\Delta t^3}{2} & \frac{\Delta t^2}{2} \\ 0 & 0 & 0 & \frac{\Delta t^3}{2} & \Delta t^2 & \Delta t \\ 0 & 0 & 0 & \frac{\Delta t^2}{2} & \Delta t & 1 \end{bmatrix} \times \sigma_a^2
$$

Where $\sigma_a^2 = 10000\frac{m}{s^2}$ is a random acceleration standard deviation, the measurements period $\Delta t = 0.1s$.

Each target can be tracked by more than one sensor. The observing measurements are collected by the sensors that surround the targets.

The measurement uncertainty $\boldsymbol{R} = \begin{bmatrix} \sigma_{x_m}^2 & 0 \\ 0 & \sigma_{y_m}^2 \end{bmatrix}$

We applied Eq. (3.5) for CS theory and the multilateration technique to compare the difference in energy consumption for each sensor. We set Δ, α, β, and μ to 0.15 m, 50 nJ/bit, 100 $PJ/(bit.m^2)$ and 2 respectively [34, 36]. The initial energy for each sensor is 5 J and $(3, 4)$ targets can appear in the sensing field. Given the sensing range, one can easily conclude that $D_{max} = 100$ m (sensing range). The colored circles represent the difference in the energy consumed by the sensors between the CS theory and the multilateration technique.

Figure 4.4,4.7,4.10, and 4.13 depicts the trajectories of targets. In Figure 4.4,4.10, and 4.13 the differences in energies consumed by the sensors between CS theory and multilateration technique are large (about 100). This is due to the slow velocities of targets (dense circles) at the start of the path. While in Figure 4.7 the velocity of the target starts slow 20 $\frac{m}{s}$, then the velocity increase to $50\ fracms$ and slows again to 20 $\frac{m}{s}$ at the end of the trajectories. This affected the energy consumed by the sensor. Figure 4.7 shows that the slow speed of the moving target causes energy consumed differences to increase between the CS theory and the multilateration technique. sensors far away from the target do not contribute to the detection and tracking of the targets, and they keep their energy. Figure 4.10 shows the trajectories of targets that are far off from one another and not shared by a set of sensors. Energy consumption for most sensors is the same for multilateration and CS approaches.

Figure 4.5,4.8,4.11, and 4.14 shows the amount of energy consumed by the sensors in the process of tracking detected targets in the field for two the detection approaches: the CS and multilateration techniques. One can see that the amount of energy the sensors spend in CS theory is less than the multilateration technique due to fusing the information of targets in CS theory.
Figure 4.6,4.9,4.12, and 4.15 depicts the projected path of all targets using collocated data from CS and the multilateration approach. In comparison to the original path, it shows how accurately the predicted path tracks with linear target trajectories.

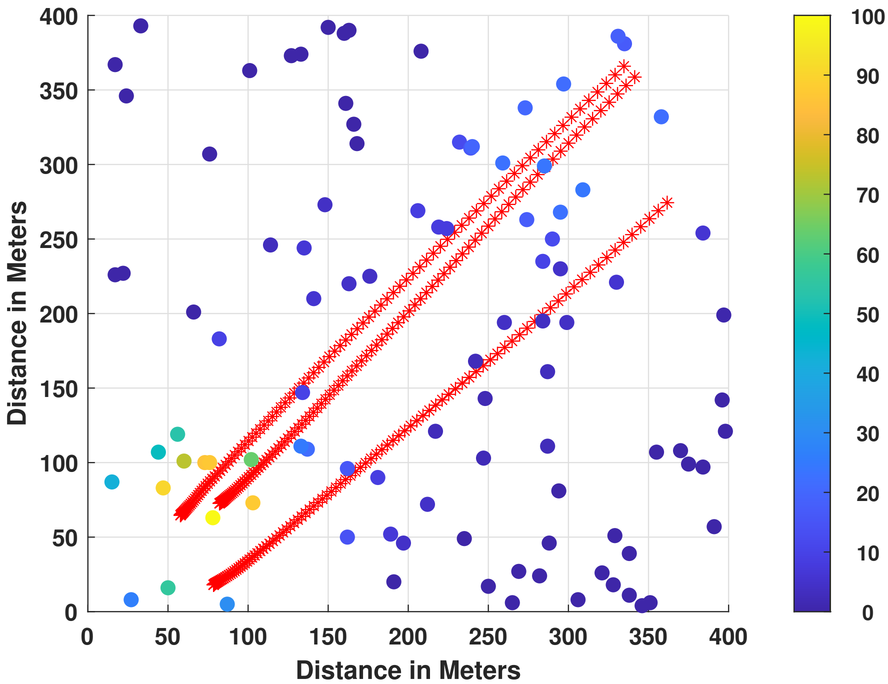


Figure 4.4: The 3 trajectories of targets. * are original trajectories of targets, the colored circles represent the sensor and the color is the difference in the amount of energy consumed by the sensors between the proposed approach and multilateration technique

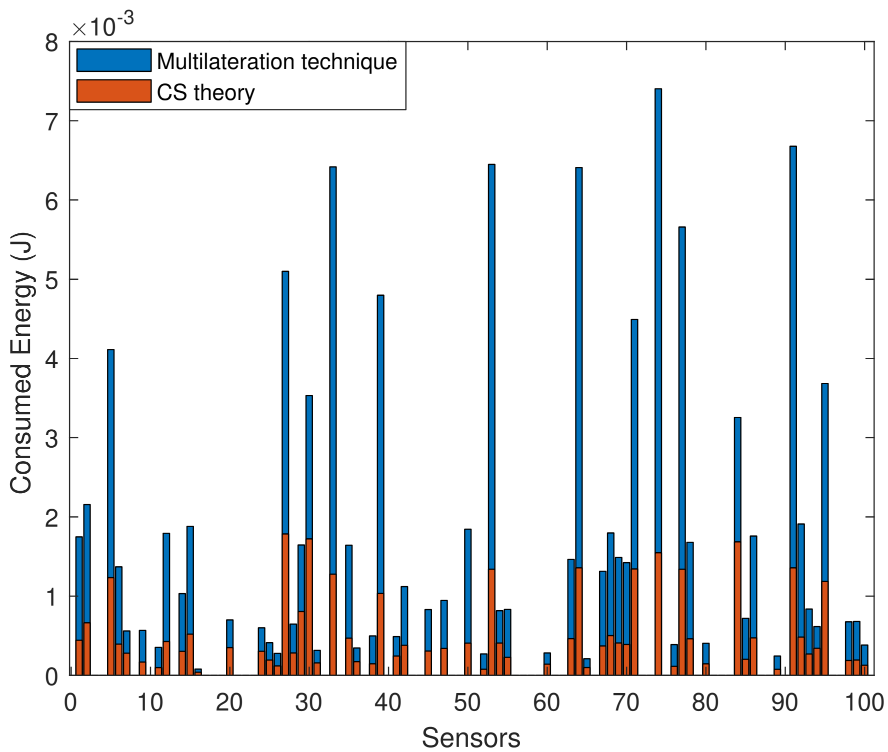


Figure 4.5: The consumed energy by the sensors to track 3 targets.

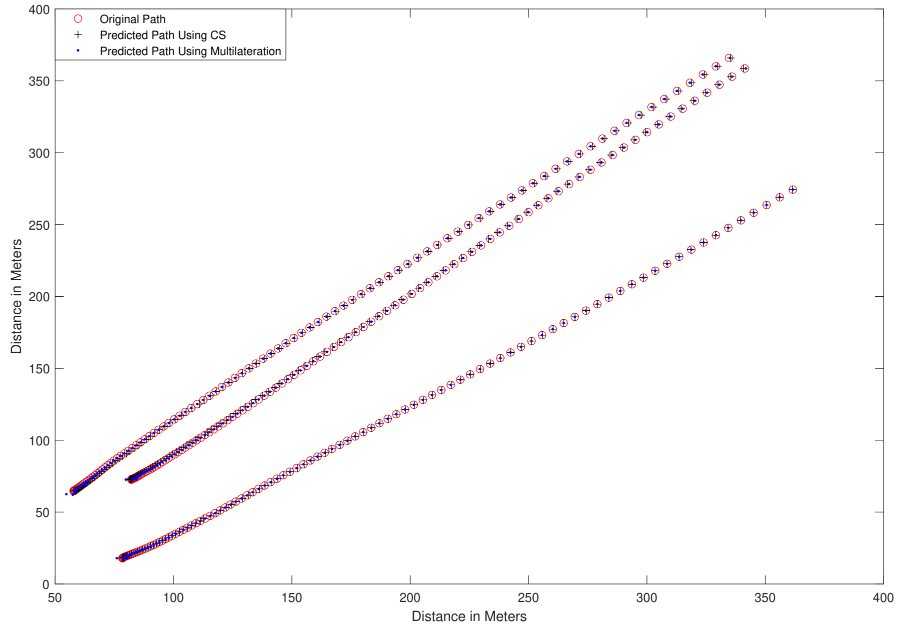


Figure 4.6: Comparison of the original and predicted path of targets .

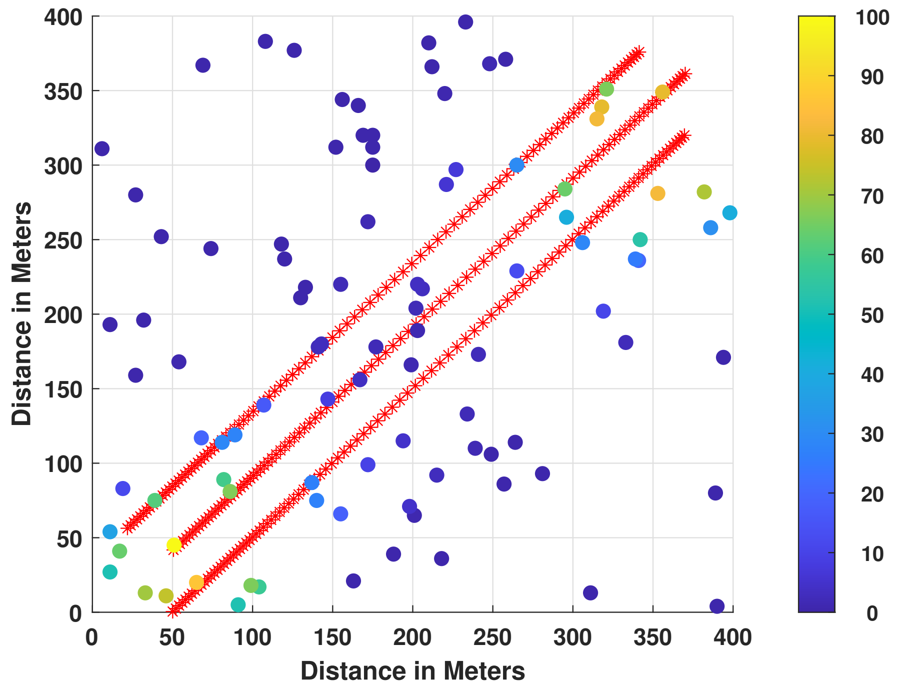


Figure 4.7: The 3 trajectories of targets. * are original trajectories of targets, the colored circles represent the sensor and the color is the difference in the amount of energy consumed by the sensors between the proposed approach and multilateration technique

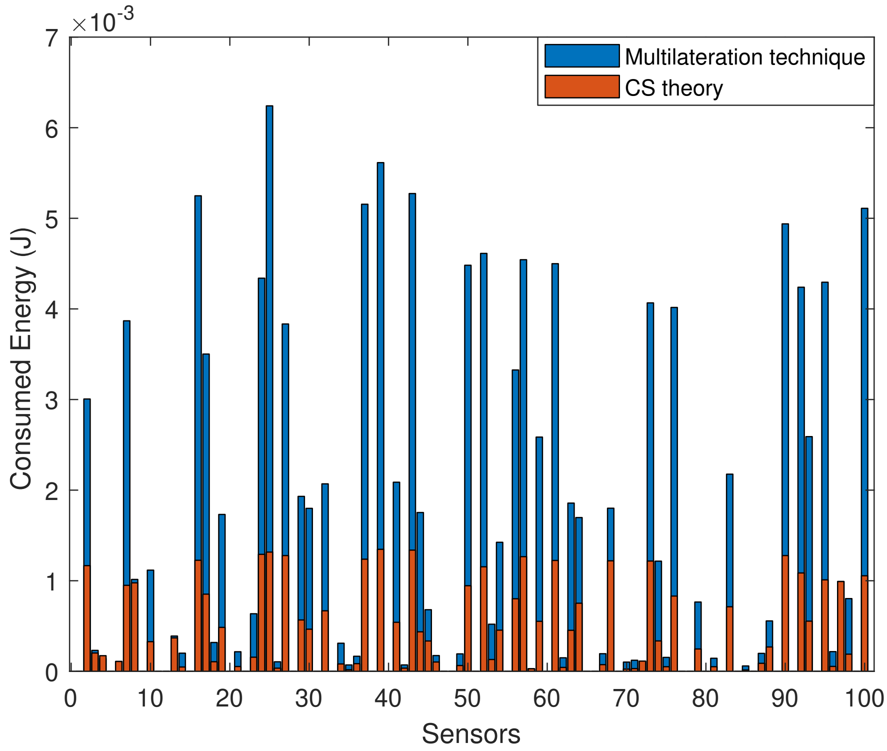


Figure 4.8: The consumed energy by the sensors to track 3 targets.

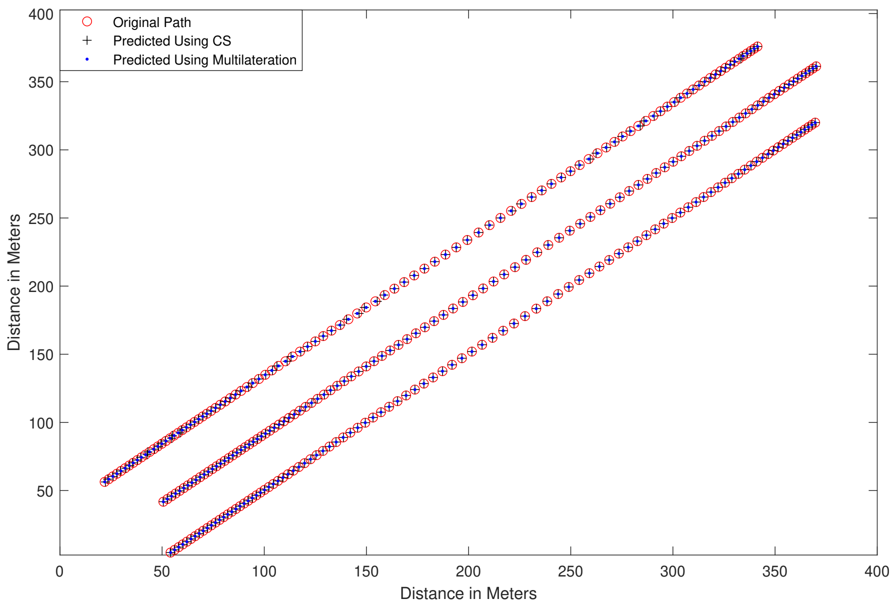


Figure 4.9: Comparison of the original and predicted path of targets .

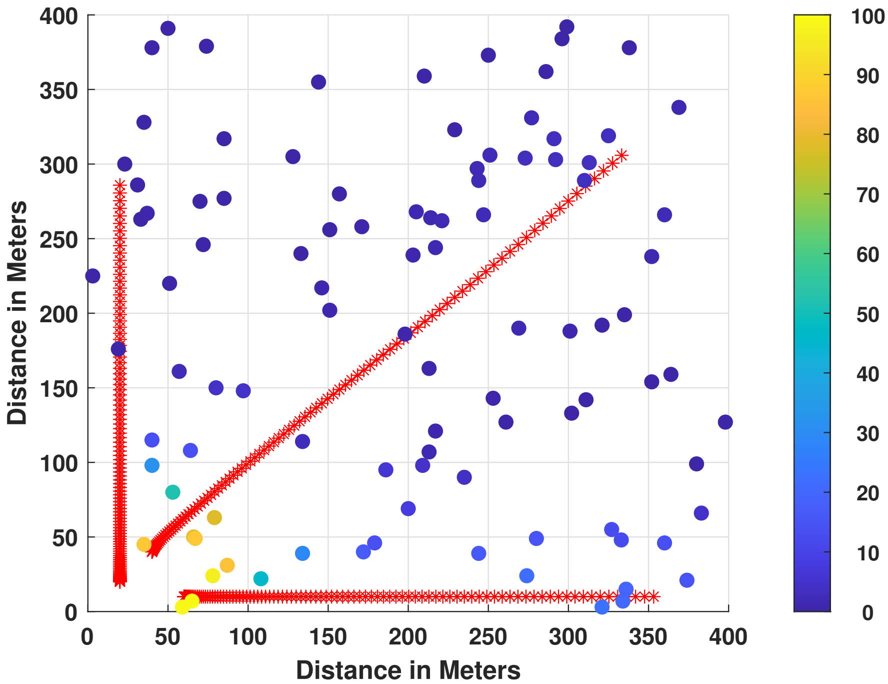


Figure 4.10: The 3 trajectories of targets. * are original trajectories of targets, the colored circles represent the sensor and the color is the difference in the amount of energy consumed by the sensors between the proposed approach and multilateration technique

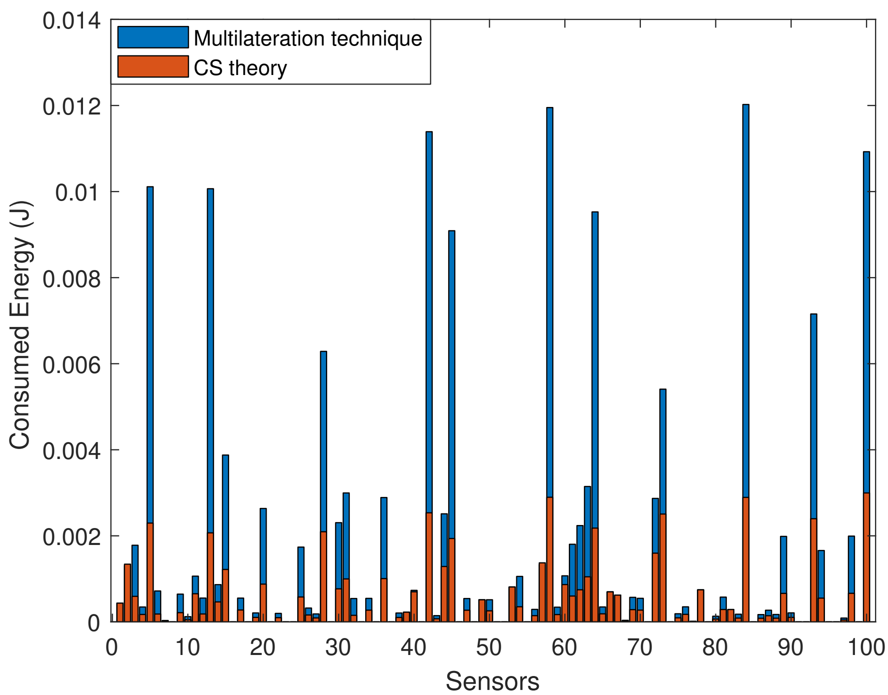


Figure 4.11: The consumed energy by the sensors to track 3 targets.

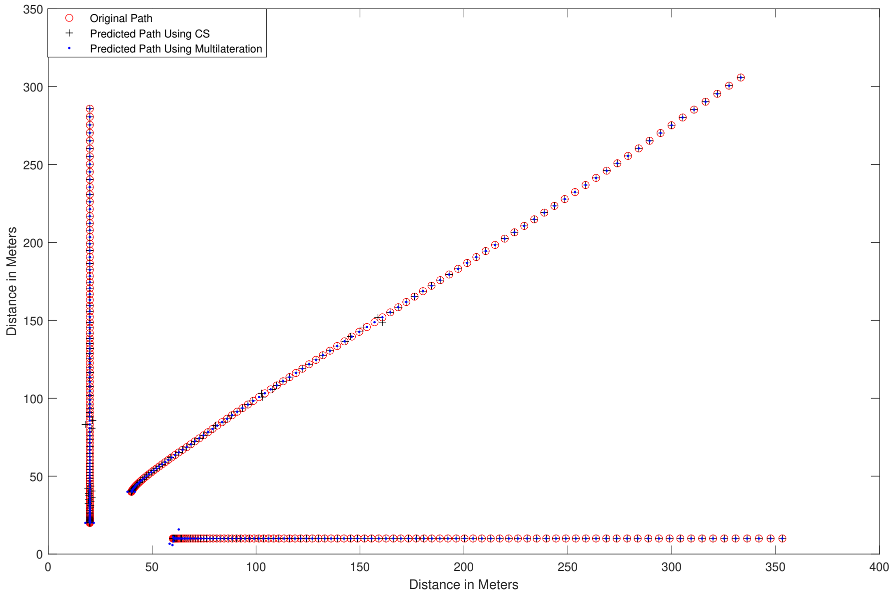


Figure 4.12: Comparison of the original and predicted path of targets .

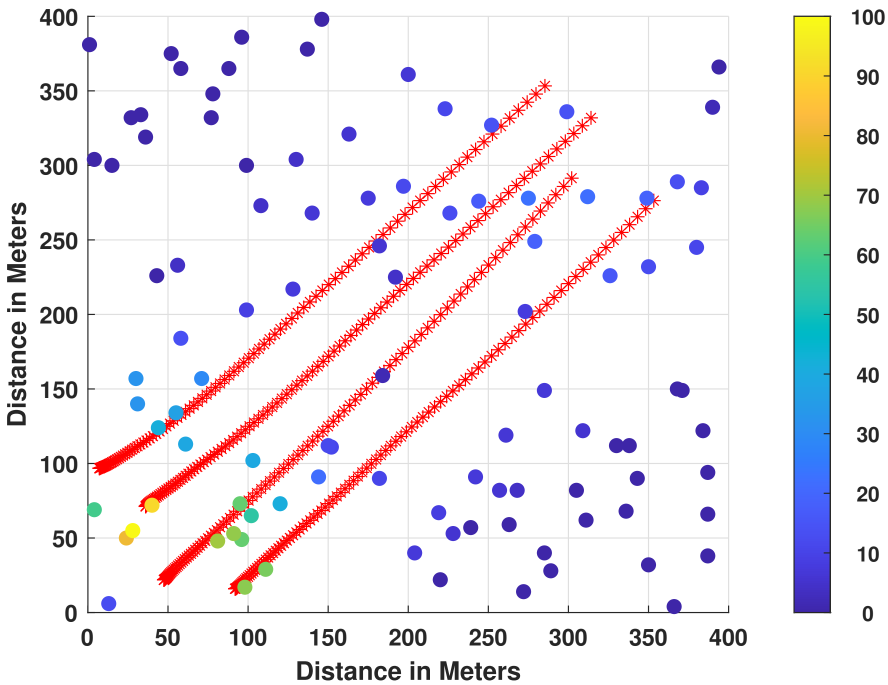


Figure 4.13: The 4 trajectories of targets. * are original trajectories of targets, the colored circles represent the sensor and the color is the difference in the amount of energy consumed by the sensors between the proposed approach and multilateration technique

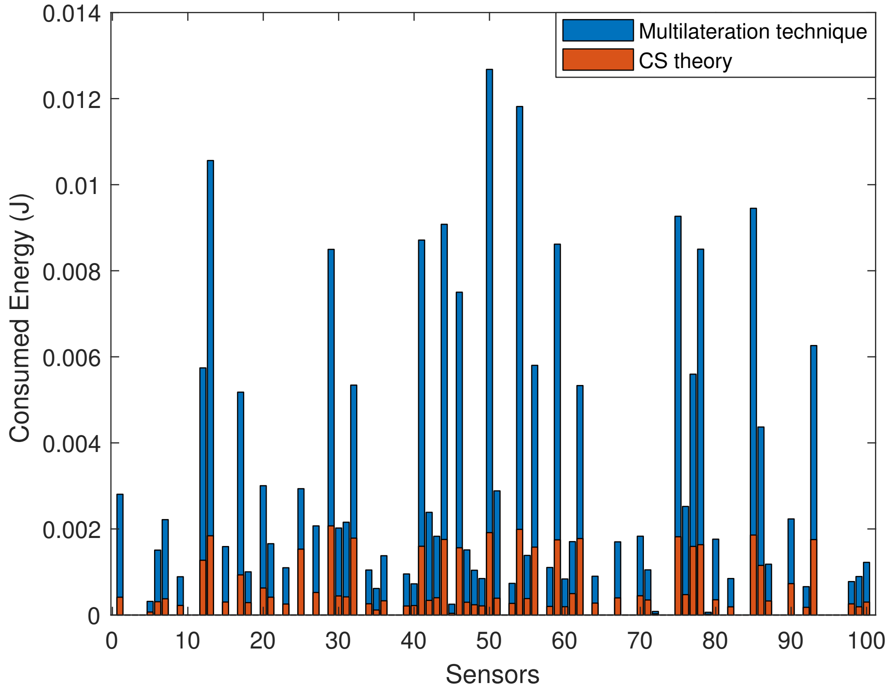


Figure 4.14: The consumed energy by the sensors to track 4 targets.

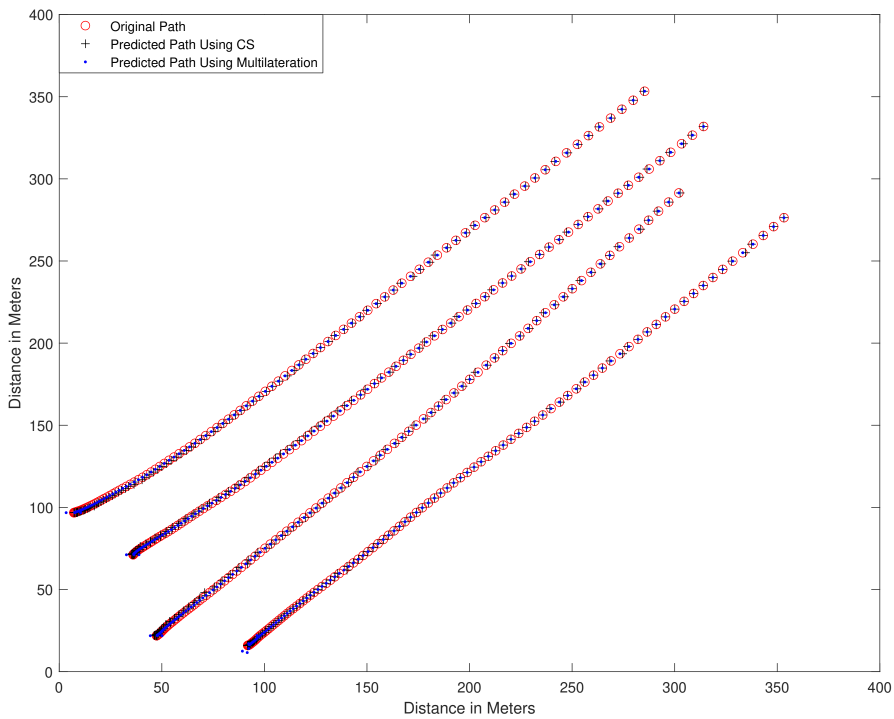


Figure 4.15: Comparison of the original and predicted path of targets .

We compare the performance of the target tracking for two collocated data models: CS theory and multilateration technique using average Mean square error (MSE) between the original path and the predicted path of the target. In Figure 4.6,4.9,4.12, and 4.15 the average MSE for estimated target trajectories of all targets measurements are summarized in Table 4.1. From the Table, we can see the tracking errors using CS theory are generally bigger than the multilateration technique for most cases. However, the average MSE for CS are small, and they fall within the acceptable ranges for most applications.

Table 4.1: Average MSE

Fig.	CS	Multilateration
4.4	0.1477	0.0672
4.7	6.2941×10^{-4}	2.4233×10^{-26}
4.10	9.019×10^{-7}	2.286×10^{-4}
4.13	0.0919	1.2909×10^{-4}

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

In light of what has been presented in the analysis of multi-target detection and tracking, the following conclusions have been arrived at:

1. For detection, a CS-based approach has been proposed. The proposed approach fuses the sensor readings for a number of the target in one packet, which reduces the number of the transmitted process required for multi-target detection compared to the traditional approach. Reducing the number of transmitted bits increases the lifetime of WSN and reduces the energy consumed in the transmission process. Simulation results show a substantial increase in WSN lifetime without compromising the detection accuracy for a relatively large number of targets compared to the traditional multilateration approach.

2. For MTT, KF is used to predict the target's trajectories. In order to save energy, the KNN algorithm has only been used to choose a portion of the sensors that contribute to MTT and to narrow the search space for the sensors that will be selected for future predictions. In each tracking step, a CS-based target detection method has been suggested for data Collection and compared to the conventional method. The suggested method consolidates the sensor readings for several targets into

a single packet, reducing the number of sent processes needed for multi-target tracking. The decrease of transmitted bits extends the lifespan of WSN, and the energy required for transmission is decreased.

5.2 Future Work

The following are some suggestions for future work for multi-target and tracking in wireless sensor networks:

1. The proposed algorithm for multi-target detection used the grid point to achieve a condition of sparse, the target appears in this grid point. We propose an approach to tackle off-grid target localization.

2. To increase accuracy, the BS can select which sensor to deliver data using an adaptive or selective CS-based approach.

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LIST OF PUBLICATIONS

1. Marwah Dhahir and Ahmed Al Hilli. Energy Efficiency Multi-Target Detection in Wireless Sensors Network via Compressed Sensing. In 6th International Conference on Engineering Technology and its Applications 2023 (iiceta 23), has been accepted in IEEE, 2023.

2. Marwah Dhahir and Ahmed Al Hilli. Energy Efficiency Multiple Target Tracking in Wireless Sensor Networks. In 4th International Conference on Advance of Sustainable Engineering and its Application-2023 (ICASEA-2023), has been accepted in IEEE, 2023.

الخلاصة

جعلت التطورات الأخيرة في تكنولوجيا الاستشعار المنخفضة التكلفة شبكات الاستشعار اللاسلكية أكثر قابلية للتطبيق على نطاق واسع. أحد التطبيقات المحتملة لشبكات الاستشعار اللاسلكية هو اكتشاف الأهداف وتتبعها. تعمل كل عقدة مستشعر في شبكات الاستشعار اللاسلكية على بطارية ، وتعتبر البطارية مصدر طاقة محدود وغير متجدد. نتيجة لذلك ، يعد تحسين كفاءة الطاقة أمرًا ضروريًا لأنه يؤثر على عمر الشبكة. تقدم هذه الأطروحة نماذج لتقليل الطاقة المستهلكة وإطالة عمر الشبكة من خلال استخدام نهج الاستشعار المضغوط للكشف عن الأهداف المتعددة وتتبعها. تقوم الخوارزمية المقترحة بدمج معلومات جميع الأهداف وإرسالها في حزمة واحدة إلى المحطة الأساسية لتقليل استهلاك الطاقة لكل مستشعر ولتقليل عدد البتات المرسلة وكذلك عمليات الإرسال عبر الشبكة ، مما أدى إلى إطالة عمر أجهزة الاستشعار محدودة الطاقة في شبكات الاستشعار اللاسلكة. في المستشعرات العملية، يتم الإبلاغ عن قراءات أجهزة الاستشعار للأهداف التي تقع ضمن نطاق الكشف للمستشعرات، ولا يتم اكتشاف الأهداف خارج هذا النطاق. لذلك، نقوم بدراسة تأثير استخدام المستشعرات العملية على عملية الكشف باستخدام استشعار الضغط. في التتبع ، يوجد حل آخر لتقليل استهلاك الطاقة للتتبع متعدد الأهداف. تُستخدم خوارزمية الجار الاقرب لتوفير الطاقة وتقليل منطقة البحث لأجهزة الاستشعار المراد تنشيطها للتنبؤات المستقبلية. يستخدم مرشح كالمان للتنبؤ بمسارات الأهداف المتحركة. تظهر نتائج الكشف عن الأهداف المتعددة ، التي تم الحصول عليها من خلال محاكاة مونت كارلو ، أن النهج المقترح يقدم انخفاضًا كبيرًا في الطاقة المستهلكة دون المساومة على دقة الكشف عن الهدف لعدد كبير نسبيًا من الأهداف ، والنهج العملي المقترح يؤدي بشكل أفضل من الحالة المثالية. تظهر نتائج التتبع متعدد الأهداف أن مخطط التتبع الخاص بنا يمكنه تتبع أهداف متعددة بشكل فعال ، ويقلل من منطقة البحث للتنبؤ في المستقبل ، ويقلل من الطاقة المستهلكة مقارنة بالخوارزميات المعقدة من الدراسات السابقة.

الكشف الأمثل عن الهدف وتتبعه عبر شبكات الاستشعار اللاسلكية

الرسالة

مقدمة الى قسم هندسة تقنيات الاتصالات كجزء من متطلبات نيل درجه الماجستير في هندسة الاتصالات

تقدمت بها

مروة اديب ظاهر

أشراف

الأستاذ المساعد الدكتور

احمد محمد زكي

2023

جمهورية العراق
وزارة التعليم العالي والبحث العلمي
جامعة الفرات الاوسط التقنية
الكلية التقنية الهندسية نجف

الكشف الأمثل عن الهدف وتتبعه عبر شبكات الاستشعار اللاسلكية

مروة اديب ظاهر

ماجستير في هندسة تقنيات الاتصالا ت

2023