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REGION UNCERTAINTY FOR EXTENDING DETECTION RANGE IN BINARY SENSOR NETWORKS

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Article Info
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Abstract
The Internet of Things (IoT) is characterized by interconnected physical entities equipped with sensors and actuators, facilitating data gathering and sharing for informed decision-making. Central to the IoT infrastructure is the Wireless Sensor Network, with Binary Sensor Networks gaining prominence over traditional models. This shift is attributed to the scalability and cost-effectiveness of deploying numerous uncomplicated devices, which operate with limited resources. Unlike conventional approaches reliant on Received Signal Strength, binary sensors offer a robust alternative by delivering binary reports based on predefined thresholds, simplifying presence detection. This binary data profoundly impacts network coverage, deployment strategies, and accuracy in localization and tracking pursuits. This study examines various problem-solving methodologies utilizing binary information, as addressed by diverse research groups.

Introduction

The Internet of Things (IoT) is comprised of networks of physical objects with embedded sensors and actuators. These objects observe their environment and share the data they collect with each other, internet servers and people. This data is analyzed and the results are used to make decisions and affect changes [1]. Wireless sensor network plays a very important role in the infrastructure of Internet of Things (IoT) [2, 3, 4].Binary Sensor Networks prevail the traditional Wireless Sensor Network nowadays due to the rationale that large numbers of simple and inexpensive individual devices are expected to be deployed or to be attached to the physical objectsfor the construction of IoT. These devices require minimal assumptions about sensing capabilities and usually come with limited resources regarding their processing capabilities, memory, and power. It alleviates the requirements of relying on the Received Signal Strength value which is known to be noisy due to the attenuation, reflection and refraction by the objects and the multi-path interference. Moreover, many sophisticated sensors or devices in traditional wireless sensor networks can also act as binary-detection devices easily by outputting a binary report with predefining a threshold for the measurements [5].This binary information indicates whether a device is present or absent within a predefined area and the range of this area directly affect the coverage and the deployment of the network, as well as the positioning accuracy in the

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widely studied localization and tracking problems.The methodology of a variety problems using binary information has been addressed by various research groups [6].

The optimal detection ranges were determined using k-NN algorithm for 1-dimensional, 2-dimensional and 3-dimensional spaces on the principle that node spacing can be derived from the detection range in [7]. These results can be used as the basis for the design of RFID-based positioning systems and other applications. However, they were obtained by minimizing the RMSE for a particular case, that is, when k-NN algorithm was used for localization. Therefore, there is no general conclusion regarding to the optimal detection range.

Optimal arrangements of binary sensors were studied in [8].The authors aimed to maximize the number of unique distinguishable sub-regions partitioned by the sensing ranges of the sensors. An upper bound on the number of unique subregions is derived to be $n^2 - n + 2$, where n is the number of sensors.

Paper [9] formulated a sensor network position estimation problem as a linear or semidefinite program, which is based on connectivity between nodes. The sensed binary information from the localneighborhood is used to build hop-based virtual distances and it is also suited for low-cost devices.Figure 1 shows a graph of connectivity of a network. The green nodes represent the reference nodes with known positions and the white nodes represent the target nodes with unknown positions. The edge represents the radio link between two nodes indicating that these two nodes are within the communicating range of each other. The objective is to localize the white nodes with the location information of green nodes and the connectivity of the network.Feasible solutions are described to the problem using convex optimization. Additionally, a method for placing rectangular bounds around the possible positions for the unknown nodes is given. However, this method requires centralized computation.Similar work on localization from connectivity can be found in [10].

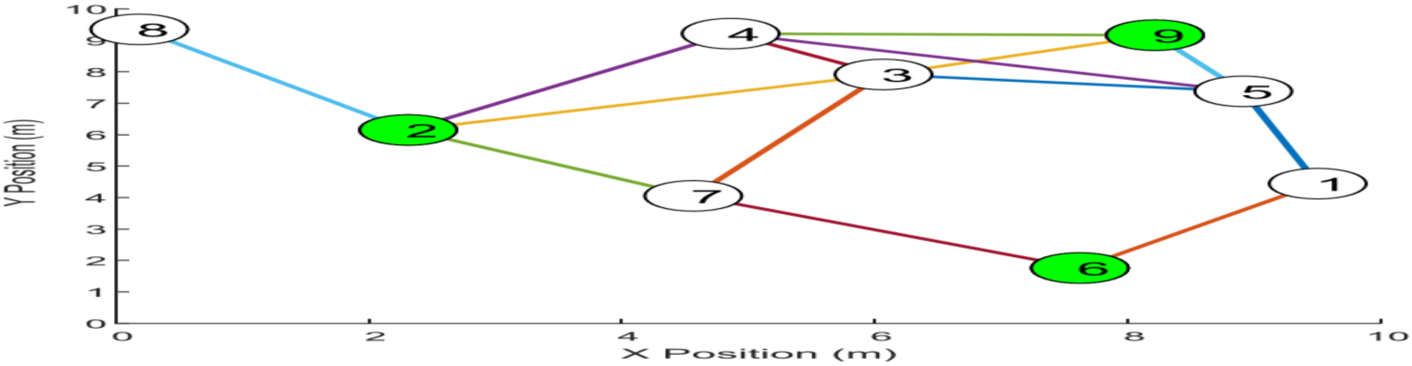


Fig. 1. Graph of connectivity of a general network.

The APIT (approximate point in time) scheme is presented in [11-12]for range-free localization, which employs an area-based approach to perform localization estimation by isolating the environment into triangular regions between nodes. It is shown that the scheme performs best when an irregular radio pattern and random node placement are considered.

A variety of analytical results were presented in [13] to aid in the design of sensor localization systems based on RSS, quantized RSS, or proximity measurements between sensors. The Crame´r-Rao bound is computed to compare the minimal attainable variances of unbiased location estimators for different cases. The results show that lower bounds for standard deviation in proximity-based systems are about 50% higher than the bounds for RSSbased systems. It is also shown that a system with just 3 bits of quantization can be enough in cases.

The remaining of the paper is organized as follows. The mathematical formulation of the optimal detection range problem is presented in Section 2, followed by a numerical method to find the minimum region uncertainty and the simulation results. In Section 3, we formulate the problem by considering two fixed thresholds. We further generalized the problem by allowing different thresholds among sensors in Section 4.The conclusion and future work are provided in Section 5.

1. With Binary Sensing

1.1. Problem formulation

We address a grid network with N by N nodes that are equidistantly located with separation distance equal to d. Let r be the distance that defines the range of the node. For a given r, the area is partitioned into several subregions. We denote the subregions by S_i, $i = 1,2,\cdots,I$ with its area being A_i correspondingly, where I is the total number of partitions in this area and A_i represents the uncertainty area when some of the nodes detect the target, which is a function of r. Clearly, if we assume that a target may be anywhere in the area with uniform distribution, the probability that the target is in S_i is given by $p_i = A_i/A$, where$A = [(N-1)d]^2$. We definethe expected uncertainty Eu when a target is in the area by

$$\begin{aligned}\mathbb{E}u &= \sum_{i=1}^{I} p_i A_i \\ &= \frac{1}{A}\sum_{i=1}^{I} {A_i}^2 = A\sum_{i=1}^{I} {p_i}^2 .\end{aligned}$$

The objective is to find the optimal r that minimizes the expected uncertainty. The problem canbe formulated as

$$\min_{r} \; A\sum_{i=1}^{I} {p_i}^2 \quad st. \sum_{i=1}^{I} p_i = 1.$$

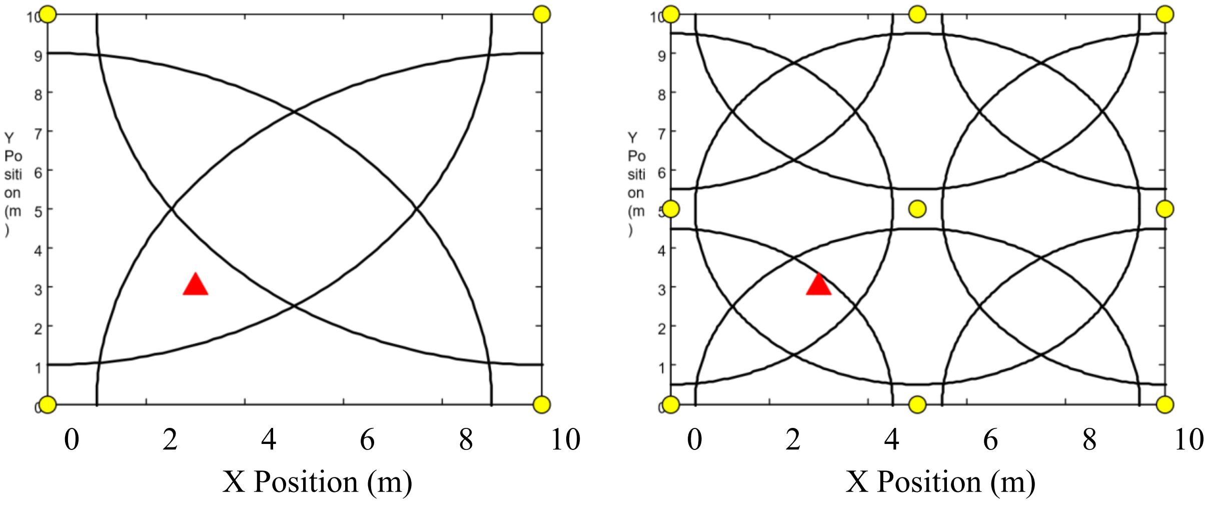
The optimal result is obtained when the region is equally partitioned, that is, when all$p_i$are the same. The resulting optimal Eu is A/I^2. Since $lim_{I\to\infty} A/I^2 = 0$, it is obvious that there's no uncertainty with large enough partitions. However, the region can hardly be equally partitioned due to geometric constraints caused by the sensing nature of the sensors.

1.2. The numeric method

The optimization problem is solved using numeric method by dividing the area into K small grids. For a fixed reading range r, we obtain a set of nodes that can detect the grid k, where $k \in 1,\cdots,K$. By counting the number of grids that have the same set (K_j, where $j \in 1,\cdots,J$and J being the total number of different sets), we obtain the probability that the target lies in a certain subregion $p_j = K_j/K$ and hence the corresponding area $A_j = p_j \cdot A$. Therefore, the values of Eu for different r are computed and the minimum Eu and its corresponding $r$are obtained.

1.3. Simulation results

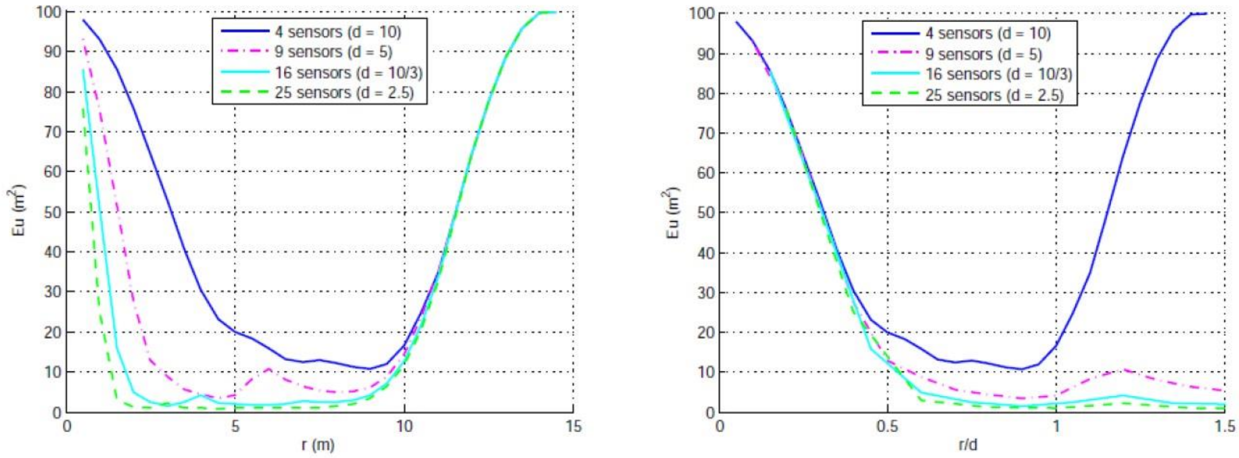
We consider a grid network with N by N nodes in a region of 10m by 10m. The examplesof a 2 by 2 and a 3 by 3 network are shown in Fig. 2.



(a) The deployment of a 2 by 2 network. (b) The deployment of a 3 by 3 network.

Fig. 2.The deployment of the grid network in a 10m by 10m region. The yellow circle represents the nodes, the red triangle represents the target and the dashed curve represents the detecting boundary.

Figure 3(a) displays *Eu* as a function of *r* with different separation distances *d*. It shows that the smaller *d* (which means the higher density) achieved smaller *Eu*. However, smaller separation distance requires more nodes, and thus the system is more expensive, especially when the nodes are the readers and antennas. This is one of the motivations that the binary devices such as proximity sensors are explored to reduce the system cost and meanwhile improve the performance. Figure 3 (b) shows *Eu* as a function of the ratio *r/d*. Since larger detecting range requires more energy and is more vulnerable to the noise, we assume that $r \leq 1.5d$, which means that the ratio is constrained to be less than 1.5. The optimal *Eu* is obtained at $r/d = 0.9$ and the results are shown in Table I. Therefore, people can set the sensing range to be 0.9 of the separation distancefor deployment in order to achieve a better localization performance.



(a) Eu vs. detecting range r (b) Eu vs. ratio r/d

Fig.3.The expected uncertainty *Eu* with different separation distances.

2. With Two Fixed Thresholds

2.1. The problem

Here we address the same optimization problem with the same network, but with each node having two thresholds. Denote the two sensing ranges to be r_1 and r_2 and let $r_1 \leq r_2$ without loss of generality. We denote the expected uncertainty as E*uu* and our objective is to minimize *Euu*:

$$\min_{r_1, r_2} A \sum_{i=1}^{I} p_i(r_1, r_2)^2 \quad st. \sum_{i=1}^{I} p_i = 1.$$

2.2. The numeric method

We solve the optimization problem using the same numeric method as that in the previous section by dividing the area into *K* small grids. To simplify the explanation, we regard the one node with two thresholds as two virtual nodes at the same location but with different sensing ranges. For the fixed reading ranges r_1 and r_2, we obtain a set of virtual nodes that can detect the grid *k*, where $k \in 1, \cdots, K$. By counting the number of grids that have the same set (K_j, where $j \in 1, \cdots, J$ and *J* being the total number of different sets), we obtain the probability that the target lies in a certain subregion $p_j = K_j/K$ and hence the corresponding area $A_j = p_j \cdot A$. Therefore, we compute the value of *Euu* for different r_1 and r_2, and find the minimum *Euu* and its corresponding r_1 and r_2.

2.3. Simulation results

We consider a grid network with 2 by 2 nodes in a region of 10m by 10m as shown in Fig. 4.

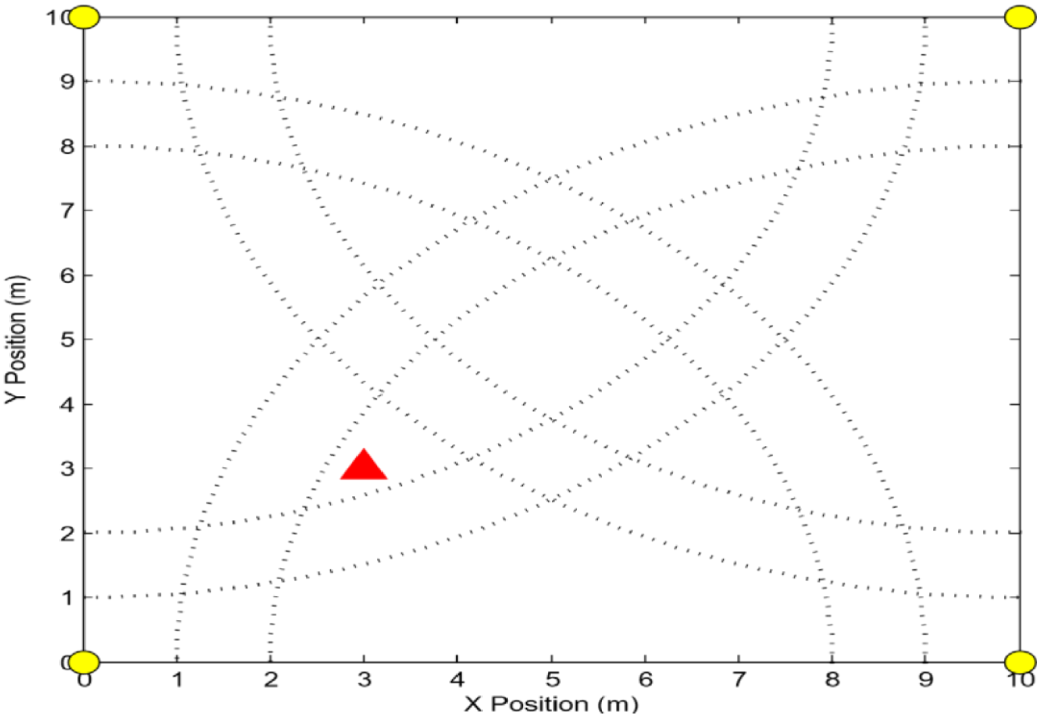
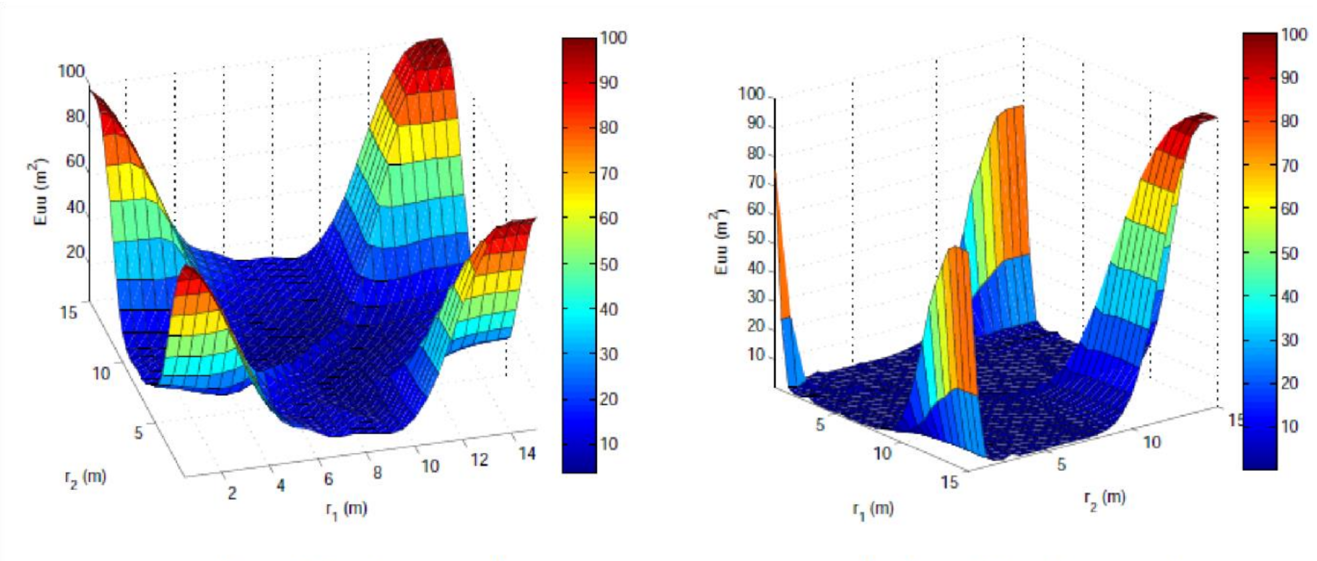


Fig. 4.The deployment of a 2 by 2 network in a 10m by 10m region. Each node has two sensing ranges.

Figure 5 displays *Euu* as a function of r_1 and r_2. Figure 5 (a) shows the result in a 2 by 2 network ($d = 10m$) and (b) shows that in a 5 by 5 network ($d = 2.5m$). The smaller d (which means the higher density) achieved smaller *Euu*. The optimal *Euu* is obtained at $r_1/d = 0.8$ and $r_2/d = 1$. The results are shown in Table I.



(a) In a 2 by 2 network (b) In a 5 by 5 network

3. **With Two Thresholds in Multiple-Stage Case**

3.1. The problem

We now consider the case of two thresholds in a sequential way, that is, we suppose at t_1 the sensing range was set to be r_1 and at t_2 the range was set to r_2. The objective is to find r_2 that minimizes the uncertainty denoted by Euu_2. In other words, the problem is to find an iterative way of choosing ranges so that the target is located as accurately as possible.

3.2. *Simulation results*

1) *Homogenous case:* In this case, the nodes are assumed to be homogenous and hence their sensing ranges are the same from each other all the time. We consider a 2 by 2 grid network as an example. Suppose the sensing range of all nodes were fixed at $r_1 = 0.9d$, then the regionwas divided into several subregions, for instance, 13 subregions as shown in Fig. 1 (a) and 4 different categories because some of the subregions are identical due to symmetry. The area of the subregions and the corresponding detecting sets by the 4 nodes are shown in Table II.

TABLE II THE MINIMUM UNCERTAINTY Euu_2

i	1	2	3	4	5	6	7
A_i	1.1666	1.1666	12.8615	1.1666	12.8615	7.5287	1.1666
Sets	{0, 0, 0, 1}	{0, 0, 1, 0}	{0, 0, 1, 1}	{0, 1, 0, 0}	{0, 1, 0, 1}	{0, 1, 1, 1}	{1, 0, 0, 0}
Euu2min	0.2950	0.2950	3.7351	0.2950	3.7351	2.1226	0.2950

i	8	9	10	11	12	13
A_i	12.8615	7.5287	12.8615	7.5287	7.5287	13.7732
Sets	{1, 0, 1, 0}	{1, 0, 1, 1}	{1, 1, 0, 0}	{1, 1, 0, 1}	{1, 1, 1, 0}	{1, 1, 1, 1}
Euu2min	3.7351	2.1226	3.7351	2.1226	2.1226	1.5676

Figure 6 shows the expected uncertainty Euu_2 at time t_2 as a function of r_2 and their minimum values, respectively. We can see that the uncertainty in the region detected by only 1 sensor achieves the minimum value 0.2950 due to the smallest area of the subregion and further division by the second range r_2. The worst case is in the region detected by two nodes with minimum uncertainty 3.7351, which is still much better than that of the binary case with a minimum value of 10.8354.

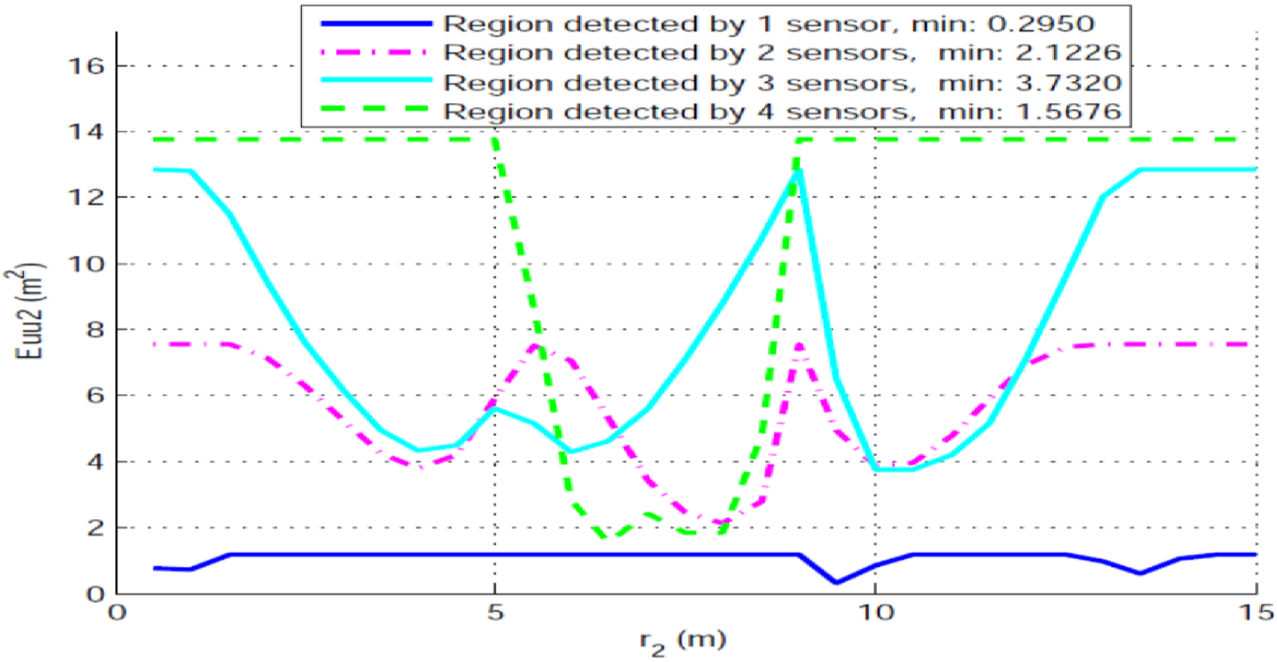


Fig. 6.The expected uncertainty Euu_2 at time t_2 when all nodes have the same r_2.

2) *Heterogeneous case:* Different from the previous case, each node can determine its own threshold at every time instant. That is, the sensing range can be different among all nodes. In this case, we might be able to partition the region equally and hence achieves the optimalvalue $A\sum_{i=1}^{I} 1/I^2$. For example, in a 2 by 2 grid network,

$Eu_{opt} = 100\sum_{i=1}^{1} 31/13^2 = 7.6923$.

At time t_2, we can also choose the ranges of the four nodes $r_2^m, m \in \{1,2,3,4\}$ so that eachsubregion from t_1 can be further partitioned equally.

4. Conclusion and Future Work

This paper investigated the problem of finding the optimal detection range of sensors/devices which generate only binary information indicating whether the target is within its proximity by a predefined detection range in the Internet of Things infrastructure. The binary information is generated by predefining a threshold for the measurements.A methodwas proposed that determines the optimal detection range by minimizing the region uncertainty.We formulated the optimal detection range problem in three different cases where in the first case, each sensor has only one fixed threshold and in the second case, the binary information was generalized to quantized value with two fixed threshold values. In the third case, the problem was further extended to the cases where the two threshold values can be determined sequentially. For each case, we showed the simulation results using numerical methods to find the minimum region uncertainty.The results show that the proposed method is feasible for achieving an optimal detection range of sensors.Our future work includes to generalize it further to an arbitrary number of thresholds with an analytical solution, to adaptthe proposed methods to anirregular network of nodes where everything is done without a central unit, andto apply the results of optimal detection ranges in a practical localization problem.

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