Non-cooperative interference radio localization with binary proximity sensors

Qihui Wu, Liang Yue, Long Wang and Guoru Ding
College of Communications Engineering, PLA University of Science and Technology
Nanjing, 210007, China
[e-mail: zgyueliang@163.com]
*Corresponding author: Liang Yue

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Abstract

Interference can cause serious problems in our daily life. Traditional ways in localizing a target can't work well when it comes to the source of interference for it may take an uncooperative or even resistant attitude towards localization. To tackle this issue, we take the BPSN (Binary Proximity Sensor Networks) and consider a passive way in this paper. No cooperation is needed and it is based on simple sensor node suitable for large-scale deployment. By dividing the sensing field into different patches, when enough patches are formed, good localization accuracy can be achieved with high resolution. Then we analyze the relationship between sensing radius and localization error, we find that in a finite region where edge effect can't be ignored, the trend between sensing radius and localization error is not always consistent. Through theoretical analysis and simulation, we explore to determine the best sensing radius to achieve high localization accuracy.

Keywords: Interference, localization, binary sensor network, sensing radius, patch

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1. Introduction

With the rapid development of economy, electromagnetic technology is now widely used in our daily life. Many daily life activities are based on the electromagnetic theory, while the spectrum bandwidth is limited, collision is not avoidable. Most of us have experienced this situation: you pick up the phone and only to find it difficult to hear clearly what the other is speaking. Interference may be the conspirator for it is an important factor that leads to bad channel conditions, then how to locate the source of interference accurately and quickly is of great importance, further consideration and study is needed.

Usually, though seriously we are suffering from the problem, we know very little about the source of the interference. We do not know where it is from and we do not know what the type is. Many unlicensed devices such as Bluetooth headsets, wireless controllers, even microwaves and WIFI devices can cause severe interference to others. Traditional work done on localization has made great progress, however, two drawbacks makes it not applicable in localizing the source of interference. Firstly, some works are based on the cooperation from the target that needs to be localized. Target will be equipped with corresponding module or offers interaction, which is not possible for interference radios. Secondly, some works need prior information about the source to identify the nature of the interfering radio, while various types there maybe, it is not that easy.

In this paper, we consider a simple and efficient method in locating the source of interference with BPSN (Binary Proximity Sensor Networks) [1]. The principle of BPSN is simple: if the target is within a sensor node's sensing range, it outputs '1', and '0' otherwise. BPSN works in a passive way which means target that needs to be located does not have to be equipped with a corresponding device, this feature makes it extremely suitable for locating the source of interference. It is practical for several reasons:

(1) Passive method with no interaction. The source of interference that needs to be located will take a resistant attitude towards localization, so a passive method without interaction is needed. GPS (Global Positioning System) is one of the most widely used systems for localization [2]. However, it works in a cooperative way that targets must be equipped with corresponding GPS module actively, which is impossible in the discussed scene. BPSN just captures the signal the target sends out quietly, no cooperation from the target is required.

(2) Localization without prior information. Binary sensors applied in BPSN only need to decide whether a target is within its sensing range, without knowing the type of the target. So in the localization stage, there is no need to identify the nature of the radio and no prior information is needed. Whatever the interference radio is, it can capture it accurately.

(3) Tiny sensors with minimal capacity required. A common method that uses RSS to locate a target highly relies on the precision of received signal strength, which suffers from an extremely time-varying and unpredictable radio channel, due to the effect of multipath, shadowing and multiphase [3]. In the BPSN, a sensor only needs to decide whether a target is within its sensing range, which is much easier and more tolerant to the dynamic nature of radio channel. Also, failure of a few sensors will not seriously affect the accuracy with the minimal information provided by a single sensor node, thus high robustness can be achieved.

(4) Energy conservation and convenient deployment. Compared with traditional complex and high-cost sensors, binary sensor works in a simple way by detecting the presence of a target, making it cheap enough for large-scale deployment. Also, under the constraints of size

and usability, sensors are usually battery powered, unable to be charged or supplied from other ways like energy harvest [4]. Binary sensor only requires limited resource, which is absolutely more energy efficient with less power consumption.

When locating a target, it is important to balance the optimization goals of precision, communication traffic and computing cost [5]. Taken the above constraints into account, BPSN stands out. As the work in [6] is done, the coverage holes is dealed with a cluster-based scheme without additional location device, for the collaborative network hepls a lot to overcome the problem of limited capacity. Similarily, though a single binary sensor is with limited sensing, processing and wireless communication capacity and can only provide minimal information for localization, a collaborative network of binary sensors can achieve good localization accuracy at a low cost in a robust manner. These cheap sensors can be deployed in a large area in a short time with simple network architecture. Low-complexity brings in the feature of fault-tolerance and longer working hour.

In the lights of these benefits, we introduce the model of binary localization in this paper. The main contributions are as follows:

- A new method to localize the source of interference with binary sensors. As far as we know, this is the first time to handle the problem of locating the source of interference with binary sensors. No interaction is required in the proposed method so target will be localized in a passive way without cooperation.
- Introduction of patch theory with a cloud-based framework proposed. With the small intersection area formed by sensing range of different sensors which is called a patch, we can locate a target in a certain area. A cloud-based localization framework is also proposed to further improve the performance. Due to its characteristics like the agility, reliability, portability, real-time and flexibility, cloud computing offloads the complex data processing from the sensor network, combination of the two gives full play to the strengths of both.

By using the geometry property, we also analyze the effect of varying sensing radius in a grid-based network. We ask a fundamental question: how to choose a best sensing radius that can achieve least localization error? We try to analyze it through theoretical analysis. We start form a one-demission space to simplify the analysis, trying to find a lower bound and inspired ideas for the 2D space. Then through simulation, we clearly understand the effect of different sensing radius in a 2D space, leading a way to more efficient utilization of BPSN. We consider the scene where there is only one target each time, leaving the situation of multiple targets to the future research.

The rest of the paper is organized as follows. Section 2 briefly reviews the research results related to this topic. Section 3 develops the model and its algorithms. Section 4 focuses on the theoretical bound with different sensing radius. In section 5, we provide the simulation results and performance evaluation. Section 6 concludes the paper.

2. Related Work

Previous studies done on localization have made great progress. Cooperative localization algorithm is a common method which can offer good localization accuracy[7]. A distributed cooperative localization is studied in [8], based on Gaussian parametric message passing on factor graph, lower communication overhead and computational complexity can be achieved. However, this can't work well in our scene for interference is always uncooperative and we must focus on uncooperative schemes.

The extensive prior work like triangulation, includes time of arrival (TOA) [9], angle of arrival (AOA) [10], time difference of arrival (TDOA) [11], roundtrip time of flight (RTOF) or received signal phase method [12]. High accuracy can be achieved with high-cost and complex sensor in these methods. However, typically, they can only work well with WIFI signals while interference radios include many types. Also, each sensor must be synchronized at a high level, and the need for strong processing ability calls for more energy requirement. Taking the versatility and cost into account, it is not that practical.

RSS-based location fingerprinting is another popular scheme [13]. Collecting data in the offline stage requires lots of time and labor, worse still, a little change in the environment can ruin the work. This method is expensive to deploy and not suitable for localizing the source of interference since there are many types and changes quickly.

The authors in [14] proposed a method to localize non-WIFI interference with commodity WIFI hardware. Prior information about the type of interference is needed to detect and identify the presence of non-WIFI devices, which inhibits the promotion since in fact there are many types of interference. Also, the localization scheme is range-based by using the received signal strength to determine the distance, which lowers the accuracy. Work done in [15] proposed a improved algorithm by computing the angle of arrival and cyclic signal strength indicator to obtain better localization accuracy. However it is still based on the identification of the source of interference at first and it requires extra DSP computation.

Owing to its simplicity and minimal communication requirements, many works has been done on target tracking with binary sensor. The authors in [16] proposed a simple method by calculating the average position of those sensors that can detect the target, which is easy to compute at the sacrifice of accuracy. An improved work is [17], which computes the weighted average of the detecting sensors' locations for coarse localization and finite localization with estimated velocity information. A tracking algorithm based on the sensors that can detect the presence or absence of a target is proposed in [18], but only a few sensor types such as sound sensors have that property. Paper [19] proposed a distributed tracking algorithm that each node computes the target's location through cooperation with neighbours, which requires high node performance. Other type of directional sensor is introduced in [20], but it is not that easy to get accurate directional information with a simple and low-cost sensor.

In this paper, we propose a new way to locate the source of interference with binary sensors and we also analyze the effect when the sensing radius of each sensor is changed in a grid-based network, seeking to find the best way to highly utilize a BPSN.

3. Network Model of Interference Localization

3.1 Binary Detection

Typically, binary sensor is a low-cost sensor with limited ability, which can only detect whether a target is within its sensing range. Binary sensor is extremely simple for it only detects the target's presence without more detailed information such as heading direction, distance or arriving angle of the target. Assume the sensing radius of a sensor is R. If a target is outside of the sensing range of a sensor, the sensor will output '0' to indicate the absence of the target. Similarly, if a target is within the sensing range, the sensor will output '1' to indicate the presence of the target. Though minimal information provided by a single sensor node, a collaborative network of binary sensors can yield good performance, which relies on statistical robustness to overcome the problem of minimal information provided by a single sensor [21], can monitor changes in the environment accurately. Compared to complex and high-cost sensor with a limited number, binary sensor is simple and inexpensive, suitable for large-scale deployment. Consider a large field without boundary effect, as the work [22] is done: localization accuracy in a binary sensor network can reach $\frac{1}{\rho R}$ where R is the sensing range and ρ is the sensor density. Many kinds of sensors have the binary detection feature, such as magnetic, seismic and sound sensors [23].

Some minimal assumptions are clarified here to simply the analysis. First, location of each sensor is known. For a grid network, sensors are deployed with predefined locations. Other self-localization technique can also be used [24]. Second, data can be accurately transmitted. For each sensor only needs to send one bit of information, the communication traffic is greatly decreased, traffic collision and packet loss can be reduced to a very low level.

3.2 Localization Model Based on BPSN

A typical model based on BPSN consists of sensors and a data fusion center. A sensor that detects a target will transmit a ‘1’ message to the data center, otherwise it will just remain silent. So the traffic can be low and such a centralized architecture can work well. With the collected data, the data center can calculate the exact location of the target in each sensing period. Huge storage and computing capacity to handle the collected data with a quick response is essential.

Sensor cloud is an emerging paradigm that integrates the cloud computing with sensor network [25]. Cloud computing turns the dream of computing as a utility into practice [26], which can provide excellent storage and processing capacity at a reasonable price with algorithm like the Kernel-based learning [27]. So the data fusion center may just be a cloud, with characteristics like the agility, reliability, portability, real-time and flexibility, which is extremely suitable for BPSN. A typical model is shown in **Fig. 1**.

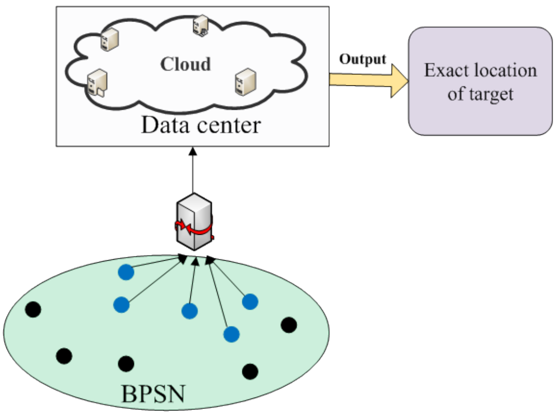

Fig. 1. Model of sensor cloud consists of the BPSN and a cloud.

Let us consider a 2D space with N binary sensors deployed in a $U \times U$ square area. The space is divided into a grid network, at the vertices of each grid, a sensor is placed. The case is illustrated in **Fig. 2**. To simplify the analysis, the sensing radius R is assumed to be same for all sensors. Let (x_i, y_i) be the coordinates of i^{th} node. MAC address of each sensor can be used as a sensor ID to represent it. The data center keeps a form of the location information of all sensors to distinguish the information provided by different sensors.

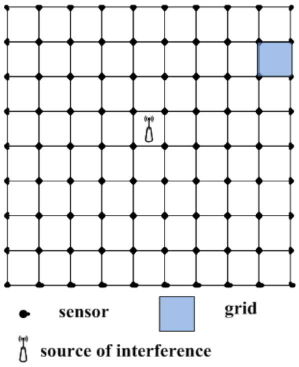

Fig. 2. A binary sensor network with sensors placed at the vertices of each grid.

3.3 The Geometry of Binary Sensor Network

For a grid based binary network, sensing regions of different sensors will intersect with each other and partition the entire region into different areas. A patch is the close area bounded by the sensing boundaries of all sensors, which consists of the intersection areas of all positive sensors that output '1' and excludes the sensing range of all negative sensors that output '0', as illustrated in **Fig. 3**. The introduction of patch theory makes it much easier to tackle the problem of localization. When a target triggers the network, a vector $\mathbf{V} = \{\mathbf{S_0}, \mathbf{S_1}, \ldots, \mathbf{S_n}\}$ is formed. If the target is within the sensing range, $S_i=1$, otherwise, $S_i=0$. Each patch is mathematically corresponding to a sense vector S. In **Fig. 3**, for example, taking the bits output by sensors 1, 2, 3, 4, 5 in that order, then patch A is corresponding to '11000', patch B is corresponding to '11100', patch C is '10100' and patch D is '01100'.

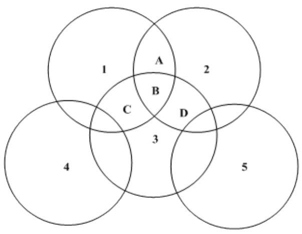

Fig. 3. Different patches in a sensor network.

We consider a practical scene where the sensing area is restricted and the edge effect can't be ignored. Localization precision is tightly related to the size of patch and different sensing radius will partition the target area into different patches.

Theorem 1 For a given network with definite target area, location accuracy is tightly related to the patches. The more patches, the more uniform of the size, the corresponding localization error is smaller.

Proof Patch is in fact a partition of the target region, each patch is mathematically corresponding to a sense vector *S*, which is exclusive. Once a patch is determined, the maximum localization error is also given, related to the size of a patch. So if there are more patches with more uniform sizes in a given region, a single patch can be small enough, the same for localization error.

3.4 Patch-based Localization Approach

The proposed theory of patch is to use geometric constraints induced by radio connectivity to decrease the uncertainty when locating a target. When a sensor is triggered, the observation indicates the target is around the sensor with a maximum distance R, so the uncertainty shrinks to a certain area. With more sensors involved, each will add a geometric constraint on the area that the target may be in, thus a promising improvement will be made with enough observations. Then we take the center of a patch as the estimated location of a target.

To save energy, sensors that do not detect the target will remain silent. In the data center, this is in fact negative information, opposite of positive information ‘1’. Actually, the absence of detection can also provide information that can be used to improve the localization accuracy. **Fig. 4** shows both the presence and absence of the target within the node’s sensing range are used to form local regions that the target may be in.

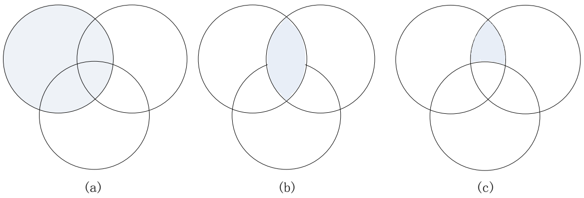

Fig. 4. Combination of positive and negative information to reduce uncertainty.

Let T denote the area the target lies in, combined with positive and negative information, it can be defined as below.

$$T = T_{pos1} \cap T_{pos2} \cap ... T_{pos\alpha} - T_{neg1} \cup T_{neg2} ... \cup T_{neg\beta} \quad (1)$$

By adding these constraints again and again, a considerable location precision can be achieved. According to the geometry relationship, some simultaneous equations can be set up to calculate the exact location of a target according to the binary readings. With the powerful computing capacity and vast storage in the data center like cloud, solution of the above equations can be calculated in an almost real-time manner and good localization quality can be achieved. An important feature of patch is that there exists one and only one vector S corresponding to each patch. Then we can take a simple approach in localization a target. It mainly consists of two steps: initial patch identification, mapping and target localization. In the first step, for a given grid-based binary sensor network, location information of each sensor node is known. Sensing data can be viewed as a matrix with predefined location information of sensors then a set of equations based on geometric constraints can be settled as (2) shows.

$$S = \begin{pmatrix} 0 & 1 & \cdots & 1 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 1 & 0 & \ldots & 1 & 1 \\ 0 & 0 & \ldots & 0 & 1 \end{pmatrix} \quad (2)$$

Method that can solve these equations can be used to get the patch and its corresponding vector and stores it in the database.

$$\begin{cases}(x-x_i)^2+(y-y_i)^2<r^2 & \forall \text{sensor i which can detect a target} \\ (x-x_j)^2+(y-y_j)^2>r^2 & \forall \text{sensor j which can not detect a target}\end{cases} \quad (3)$$

In the second step, during a sensing interval, after a sensing vector is transmitted to the data center, a mapping between the received vector S and the patch is executed, by comparing *S* with the predefined *S'* in the database. The mapping can be done in a very quick way with high precision, then truly real-time can be achieved. The procedure is illustrated in **Fig. 5**. This is in fact an ideal model, in practical scenes affected by noise, the practical scene is a bit different, which is analyzed in the next chapter.

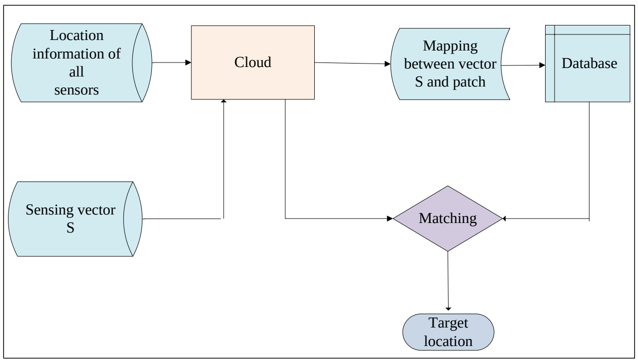

Fig. 5. Mapping between sensing vector and predefined vector in a cloud based data center.

4. Bound of Localization Error

4.1 Threshold for Different Sensing Radius

It is clear that sensing radius plays a decisive role in determining the quality of the separation. Generally, the received signal strength ζ_i at sensor *i* is related to the distance from the source. Sensing range of a binary sensor is small and we can take the assumption that there is no change in the propagation, then we can take the isotropic model

$$\zeta_i=\frac{\zeta_0}{(\frac{d_i}{d_0})^{\alpha}}+\omega_n \quad (4)$$

Where ζ_0 is the power of the target measured at reference distance d_0, and d_i is the Euclidean distance from the source, as (x_i, y_i) denotes the coordinates of the sensor, (x_s, y_s) denotes the coordinates of the source, we can get

$$d_i=\sqrt{(x_i-x_s)^2+(y_i-y_s)^2} \quad (5)$$

In a practical environment, noise is inevitable. As most of the studies have done, we take the noise as Gaussian white noise, $w_n \sim (0, \delta_w^2)$.

For binary sensors, in fact a threshold is used to decide if a target is within the sensing range. If the value is above (below) the threshold, the target is determined to be within (outside) the sensing radius. Let H defines the power threshold, which can be defined below

$$Value = \begin{cases} 1, & \zeta_i > H \\ 0, & \zeta_i < H \end{cases} \tag{6}$$

The adaptive threshold can be calculated in the data center and distributed to all the sensors in an idle state. Given a threshold H, we can get the sensing radius

$$R = \sqrt[\alpha]{\frac{\zeta}{H}} \tag{7}$$

By adjusting the threshold in a dynamic manner, then we can get different sensing radius to form different patches, thus different localization accuracy can be achieved. However, noise may have severe influence on localization when the sensing range grows to be large, which may lead to a false detection or missing detection. And it is obvious if the sensing radius gets larger, we have to adjust the threshold to a lower value and it is more vulnerable to the noise. According to [28], given a threshold H and the probability of wrong detection

$$H = \delta_w \sqrt{2} erf^{-1}(1-2P) \tag{8}$$

then we can get

$$P = \frac{1}{2}(1- \operatorname{erf}(\frac{H}{\delta_w \sqrt{2}})) \tag{9}$$

where *erf* is the standard error function

$$erf(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt \tag{10}$$

In order to alleviate the impact of noise, we can take the model in [29] to improve accuracy

$$H_k = \begin{cases} H_{k-1} \times (1-\beta) + \psi \times \beta & if \ s(\tau) = 0 \\ H_{k-1} & otherwise \end{cases} \tag{11}$$

Here β is the forgetting factor and ψ is the smoothed magnetic signature and $s(k)$ is the detection sequence. Also, location information of sensors is also an important factor that can be used to overcome the impact of noise. An important feature of binary proximity sensors is the valuable location information of sensors. When all the sensing data is received in the data center, we can simply filter the data by taking advantage of the proximity feature to eliminate the effect of data that is obviously wrong and better localization accuracy can be achieved. Generally, if a positive sensor lies far away from other positive sensors, we can deduce that it is a false alarm, so we can correct the wrong sensing reading to a right one, as **Fig. 6** shows. A similar case is when a sensor is surrounded by positive sensors while its output is ‘0’, we can view it as a missing detection.

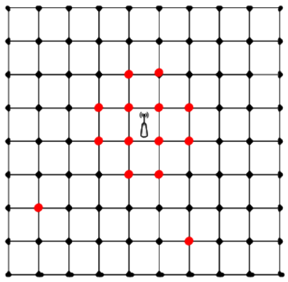

Fig. 6. Two positive sensors far away from other sensors can be viewed as false alarm. An simple algorithm can be used to eliminate the effect when locating a target in the data center.

4.2 Effect of Localization with Different Sensing Radius

Different sensing radius will partition the entire region into different patches, which is tightly related to the localization error. In order to analyze the effect in a simple way, we first focus on a one-dimensional space, as the work in [1] is done. Suppose there are N binary sensors deployed in a straight line, each with a sensing radius R, the length between adjacent sensor nodes is L. Then we try to evaluate the lower bound of varying sensing radius from this one-dimensional space, seeking to find a rule that can be applied in a 2-D space.

In a one-dimensional space, different sensing radius will have different effect. We firstly take the case when $R \in (0,\ L/2)$, as **Fig. 7(a)** is shown, sensing range of adjacent sensor nodes is never intersected, leaving a certain distance in the line where target within it will never be sensed, let alone localization, this is the meaningless case. A basic rule for a binary sensor network is that sensing range of adjacent sensor nodes will intersect.

Fig. 7(a). When sensing radius is less than L/2, sensing regions of all the sensorswill not intersect with each other.

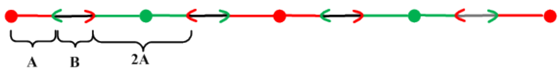

Fig. 7(b). When sensing radius is between L/2 and L, only adjacent sensors' sensing regions will intersect with each other.

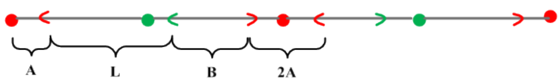

Fig. 7(c). When sensing radius is between L and 3/2L, more sensing ranges will be involved.

Let us consider a more practical scene where $\mathrm{R} \in (\mathrm{L}/2, \mathrm{L})$, as **Fig. 7 (b)** shows. We define the average distance between the actual coordinates and estimated coordinates of a target as the localization error Eε, the probability the target may be in a certain distance is P, then we have

$$E_\varepsilon = E_A P_A + E_B P_B + E_{2A} P_{2A} \tag{12}$$

and in this case, it is

$$E_{\varepsilon 1}=2\times\frac{A}{4}\times\frac{A}{(N-1)L}+(\text{N-1})\times\frac{B}{4}\times\frac{B}{(N-1)L}+(N-2)\times\frac{2A}{4}\times\frac{2A}{(N-1)L} \tag{13}$$

When R grows to be $R\in(L,3/2L)$, as **Fig. 7 (c)** shows, we can get

$$\begin{aligned}E_{\varepsilon 2}=&2\times\frac{A}{4}\times\frac{A}{(N-1)L}+(\text{N-3})\times\frac{B}{4}\times\frac{B}{(N-1)L}\\&+(N-4)\times\frac{2A}{4}\times\frac{2A}{(N-1)L}+2\times\frac{L}{4}\times\frac{L}{(N-1)L}\end{aligned} \tag{14}$$

Compare (13) and (14), it interesting to find that

$$\begin{aligned}E_{\varepsilon 1}=&2\times\frac{A}{4}\times\frac{A}{(N-1)L}+(\text{N-3})\times\frac{B}{4}\times\frac{B}{(N-1)L}\\&+(N-4)\times\frac{2A}{4}\times\frac{2A}{(N-1)L}+2\times\frac{B+2A}{4}\times\frac{B+2A}{(N-1)L}\\E_{\varepsilon 2}=&2\times\frac{A}{4}\times\frac{A}{(N-1)L}+(\text{N-3})\times\frac{B}{4}\times\frac{B}{(N-1)L}\\&+(N-4)\times\frac{2A}{4}\times\frac{2A}{(N-1)L}+2\times\frac{L}{4}\times\frac{L}{(N-1)L}\end{aligned} \tag{15}$$

The above equations only differ in the last item, in fact it is easy to find that $B+2A=L$. We can conclude from this: $E\varepsilon 1<E\varepsilon 2$. For in (14), the L is divided into two parts: B and 2A while in (15) it is taken as a whole. According to *Theorem 1*, finer division will lead to better results. If R keeps increasing, it not difficult to find that more division of 'B' and '2A' will become a whole 'L', surely the localization error increases as well.

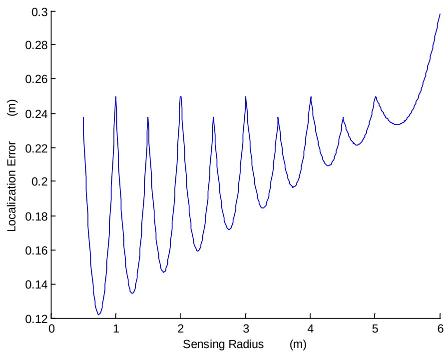

Fig. 8. Theoretical analysis of localization error in a one-dimensional space.

From the aspect of one-dimensional space, there are different cases when the value of R varies, such as the three cases illustrated above, and each case corresponds to an interval of value segment of the sensing radius R. According to the above equations, we operate the theoretical analysis and the results are shown in **Fig. 8**. During each segment, an optimal solution can be achieved and the general trend of optimal solution is monotonic, just as can be seen from **Fig. 8**. Then we may conclude from the figure that when R increases, the minimal error at each interval will increase at the same time. To simply the analysis which may be very complicated in a 2D space, we try to start from the one-dimensional space to reveal the certain trends. The analysis in the view of one-dimensional space further verifies the correctness of Theorem 1, indicating that finer division of the field will lead to more patches, thus better localization accuracy can be achieved. Different from the one-dimensional space that larger R will deteriorate the division, when the value of R changes in a 2D space, a small increase of R can lead to a giant increase in patches, which nearly grows in the exponential manner. So the situation is much more different in a 2D space, which we can see from the simulation.

5. Simulations

In this section, we carry out the simulations to evaluate the performance of the proposed algorithm and verify the impact of different sensing radius in a 2D space. In all the cases, the field is a $10m \times 10m$ square, divided into grids and sensors are deployed in all the vertices of the grids. Length of the grid is fixed, which we set to be 1m here, while the sensing radius R ranges from 1m to 10 m. All results were averages of 1000 independent runs.

Our algorithm proposed takes advantage of the proximity feature to ensure accuracy. It seems as if larger sensing radius will lower the resolution for a sensor can only locate a target in a larger area, however, this is not that true. For if we view this from another aspect, a larger sensing range can also make sure more sensors can detect a target at the same time, according to (1), a small increase in a single sensor node's uncertainty may lead to a much more decrease in uncertainty when we take a network of sensors that works in a collaborative way into account. Theoretically, if the sensing radius is more than L/2, sensor nodes' sensing ranges begins to intersect in the space. With larger radius, more sensors will detect the target, and the whole sensing field will be partitioned with finer degree, more patches will be formed, the average size of patch decreases as well, then the localization error determined by patch decreases at the same time. This is because though less information provided by a single sensor, a collaborative network of binary sensors can performance better which is balanced by a quadratic increase in the number of patches. The connectivity feature is fully utilized in this method, and for comparison, the performance of Centroid method and APIT method [30] based on the connectivity principle are also shown here. The Centroid method simply averages the coordinates of sensors that detect the target as the estimated location of the target, while the APIT method performs location estimation by isolating the environment into triangular regions between beaconing nodes. As can be seen from **Fig. 9**, as the connectivity degree increases, more sensors far away from the target will be involved, localization accuracy in the Centroid method will decrease. While better connectivity will improve the performance of both the APIT method and our method, a finer division of the sensing field of our method outperforms the APIT method.

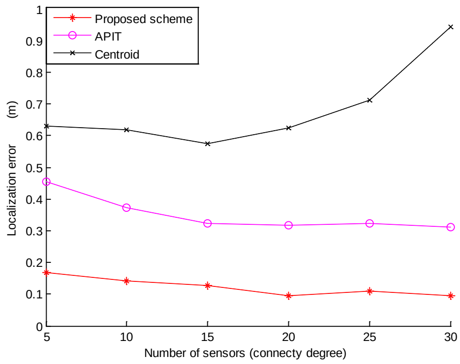

Fig. 9. Performance comparison under different connectivity degrees.

Later, we consider a more practical scene that edge effect can't be ignored. When the sensing radius is above half of the length of the area, namely, U/2, the central part of the sensing region begins to form a large patch, size of which increases with sensing radius, as can be seen from **Fig. 10**. An extreme example is when the sensing radius is big enough for every sensor to cover the space, then the whole region will become a single patch, information behind these data is far from enough to locate a target. Under this circumstance, the number of patches does not grow as the sensing radius increases, so the trend of localization error will also change.

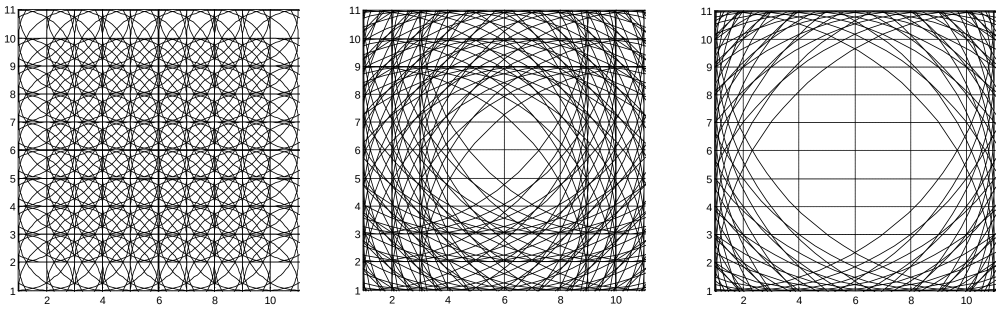

Fig. 10. Patch forming with sensing radius: 2m, 7m and 10m.

When we come to a practical scene with noises, the situation will be different. Surely, the error of observation is highly related to the accuracy of localization for incorrect observation will lead to a wrong sensing vector *S*. Since each *S* is corresponding to a patch, a wrong sensing vector will lead to the wrong patch, thus comes to lower localization accuracy. Let e% denotes the number of sensor nodes which can detect the target that make wrong observations, **Fig. 11** shows the experimental results with various values of e when the data are not filtered with location information of sensors. It is easy to observe that higher sensing error will lead to higher localization error.

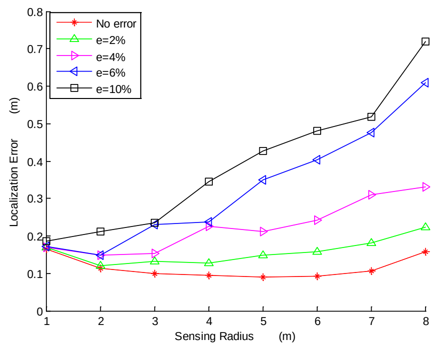

Fig. 11. Localization error under different observation error € with varying sensing radius.

Added with location information of the sensors, we can correct the reading of sensors that are affected by noise to some extent as the case in shown in **Fig. 6**. Localization accuracy will be much better improved for the mapping will be much more precise, as is shown in **Fig. 12**.

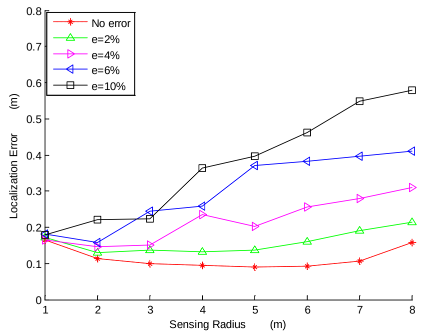

Fig. 12. Localization error under different observation error € with varying sensing radius after data filtering.

We can see from the above simulation results that, theoretically, in an ideal environment, the optimal sensing radius is about U/2, where U is the side length of the space of interest. But we can conclude from the simulation results when sensing radius grows from U/3 to U/2, the location accuracy won't improve at a significant level while the computation cost will increase a lot and more vulnerable to noise in a practical scene. So taken the factors of cost and fault-tolerance into account, we can set the optimal sensing radius to be U/3, then both good localization accuracy and low cost can be achieved.

6. Conclusion

In this paper, we consider a simple approach to locate the source of interference in a passive way with a binary sensor network. We consider the problem of locating it with different sensing radius and analyze the geometrical influence on patch forming. We are dedicated to explore the basic bounds of localization errors from a one-dimensional space in order to gain basic rules. Results show that when sensing radius is about half the length of the space, best localization accuracy can be achieved, taking the cost into account, we find a third of the length can be chosen as the best sensing radius, leading a way to more efficient utilization of binary sensor networks in the field of interference localization.

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Qihui Wu received his B.S. degree in communications engineering, M.S. degree and Ph.D. degree in communications and information systems from Institute of Communications Engineering, Nanjing, China, in 1994, 1997 and 2000, respectively. From 2003 to 2005, he was a Postdoctoral Research Associate at Southeast University, Nanjing, China. From 2005 to 2007, he was an Associate Professor with the College of Communications Engineering, PLA University of Science and Technology, Nanjing, China, where he is currently a Professor and Ph.D. supervisor. From March 2011 to September 2011, he was an Advanced Visiting Scholar in Stevens Institute of Technology, Hoboken, USA. His current research interests span the areas of wireless communications and signal processing, with emphasis on system design of software defined radio, cognitive radio, and spectrum management.

Liang Yue received the B.S. degree in Changsha University of Science and Technology, Changsha, China, in 2013. He is currently pursuing the M.S. degree in communications and information system at College of Communications Engineering, PLA University of Science and Technology, Nanjing, China. His research interests are wireless sensor networks and localization.

Long Wang received the B.S. degree in electronic information science and technology from Tsinghua University, Beijing, China, in 2010, and the M.S. degree in communication and information systems from the PLA University of Science and Technology, Nanjing, China, in 2013. His current research interests include femtocell networks, wireless sensor networks, and big data analytics.

Guoru Ding received the B.S. degree (Hons.) in electrical engineering from Xidian University, Xi'an, China, in 2008. He is currently pursuing the Ph.D. degree in communications and information systems at College of Communications Engineering, PLA University of Science and Technology, Nanjing,China. His research interests include cognitive radio networks, machine learning, statistical signal processing, and big data analytics over wireless networks. Mr. Ding currently serves as a Technical Program Committee (TPC) member of IEEE GLOBECOM 2014 and IEEE VTC 2014-Fall. He is an invited reviewer for more than 10 journals such as IEEE Signal Processing Magazine, IEEE Communications Magazine, IEEE TRANSACTIONS ON COMMUNICATIONS, and IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, etc. He was a recipient of the Best Paper Award from IEEE WCSP 2009. He is a ACM student member and was a voting member of IEEE 1900.7 White Space Radio Working Group.