Probabilistic Exposure Identification for Wireless Sensor Network

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Abstract

Sensing and coverage are the two most relevant tasks for a sensor network. Wireless sensor network performance entirely depends on the success of sensing and detecting any object over a monitored region. Network performance may always degrade due to the limited energy and computation capability of sensors. So, it is a crucial task to identify those humiliations of sensors in a network. Exposure path is a probabilistic concept and it determines the probability of detecting any object by the sensors. In this paper we proposed a new algorithm to find out the minimum exposure path in a particular region of the network. It is totally a graph-theory as well as a convex geometry based approach. In order to improve the network performance the minimum exposure path algorithm of this paper can perform an appreciable role. Moreover the use of closest sensor of a cluster makes the overall computation less expensive for the proposed algorithm. Finally, we analyzed the proposed algorithm with some numerical simulation in order to obtain an approximate minimum exposure path.

1. Introduction

Wireless sensor networks are a hastily striking resource to scrutinize the environmental conditions where people wish to implement their thoughts, expertise applications etc. As a result deployment, re-deployment and structuring of a sensor network in a target area can be an incessant practice. Deployment and re-deployment can be as diverse as establishing one-to-one relationships by attaching sensor nodes to specific items to be monitored [1], covering an area.

In case of network coverage, detecting any object over a sensing region is measured by exposure. Exposure is a probabilistic concept and in a sensor network it depends on the probability of detecting any object by the sensors [3]. That means by calculating exposure path we can simply identify the worst-case coverage or best-case coverage of a network. Accordingly, to improve the network performance exposure path identification can play a significant job.

Computation is one of the critical aspects for the exposure calculation. Accordingly we have proposed an analytical solution for exposure calculation with the aid of graph theoretic approach. In order to find a minimum exposure path, our first target is to divide the network in to certain optimal clusters. For our proposed exposure path estimation algorithm the whole network is thought to be a Voronoi diagram based network. From the higher point of view each cluster of the network considered as a point inside Voronoi convex polygon. The main aspiration of the proposed approach is to find the least probability of detecting any object over a Voronoi diagram based network by the deployed sensors. Then based on the least probability of detecting any object on each Voronoi edges we have to find out the shortest path for a given source and destination.

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2. Related Work

It is mandatory to mention that lots of research is going on for finding both the least and most coverage path of a sensor network [2, 3, 4, 5, 7]. So far two definitions of least coverage path are exposed: Maximal Breach Path [7] and Minimum Exposure Path. According to [3], for a pair of points the minimum exposure along their line segments have to found on which there should be some sensor intensity. On the other hand in [5], neighboring nodes are updated with the new path calculation for finding the minimum exposure path. Both [3] and [4] follow the grid-based network. The main problem in grid-based network for exposure calculation is that, the path is to map either on vertical edges or on horizontal edges or on diagonal edges of the grids. As a result the total computation and complexity becomes too high for large number of grid points in a network.

Moreover for the centralized approach proposed by Seapahn Meguerdichianl et.al. [3], no use is made for the Voronoi approximation. But in another paper [7] by the same authors showed the improvement and degradation of network by calculating maximal support path and maximal breach path with the aid of convex geometry. In the localized approach proposed in [4] still have some questions about the optimality for the minimum exposure path calculation.

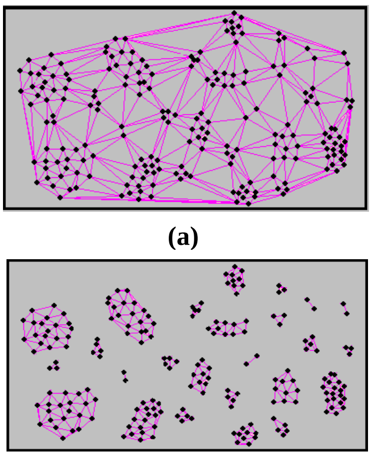
3. Clustering Algorithm

The clustering algorithm used here is based on Delaunay triangulated sensor nodes. The key idea of this clustering method is taken from the clustering method used for key frame-based video summarization technique [6]. But we have made the referred clustering algorithm suitable and applicable for sensor network. This is an efficient clustering method in comparison to other clustering method.

A network discontinuity for a Delaunay Triangulation based network can be identified using the inter-cluster edges. In this algorithm our target is to find all the inter-cluster edges in the network. Thus this clustering method ends by removing the inter-cluster edges and we get some unique clusters. Variability of different parameters of edges such as: edge length, local mean length of the edges, and local standard deviation of the edges make the identification of inter-cluster edges easier. One important criterion is that, always inter-cluster edges are larger than the intra-cluster edges.

Algorithm: Cluster (N)

1. **for** a given set of nodes $N_i = \{n_1, n_2, \ldots, n_p\}$ in the network where $p \geq 2$,
   Generate Delaunay Triangulated Graph G
2. **for** each node $N_i = \{n_1, n_2, \ldots, n_p\}$ in G
   if N_i== new node **then**
   for each edge e_j incident to node N_i
   Calculate local mean edge length,
   $$L(N_i) = \frac{1}{d(N_i)} \sum_{j=1}^{d(N)} |e_j|$$
3. **Calculate** the local standard deviation of length of each edges incident to node N_i,
   $$LD(N_i) = \sqrt{\frac{1}{d(N_i)} \sum_{j=1}^{d(N_i)} (L(N_i) - |e_j|)^2}$$
4. **Calculate** mean of local standard deviation,
   $$GD(N) = \frac{1}{p} \sum_{i=1}^{p} LD(N_i)$$
5. **Define** $Intra\text{–}Cluster\_Edge(N_i) = \{e_j \mid |e_j| < L(N_i) - GD(N)\}$
6. **Define** $Inter\text{–}Cluster\_Edge(N_i) = \{e_j \mid |e_j| > L(N_i) + GD(N)\}$
7. **Remove** all Inter-Cluster Edges



(a)

(b)

Fig. 1. (a) Delaunay Triangulated Network and **(b)** Network after removing the Inter-cluster edges.

4. Procedural Fundamentals

Based on sensing intensity of sensors we can calculate the exposure of randomly chosen points of a path. A Voronoi edge is certainly common between at least two clusters and has some intensity due to the sensors. So it is certain that these Voronoi edges have minimum exposures than any other edges or region in a network [9].

4.1 Cluster Sensing Model

Let s is a sensor of a cluster C and p is an arbitrary point of any incident Voronoi edge. Thus the cluster sensing model can be defined as [3]:

$$S(s, p) = \frac{1}{[d(s_{\min}, p)]}$$

Where $d(s_{\min}, p)$ is the Euclidian distance between the closest sensor of the cluster C to the point.

4.2 Common Cluster intensity function

The intensity of a particular point is equal to the summation of the two closest sensor intensity of each cluster. Let a sensor field with several clusters and a point p over a Voronoi edge then the common cluster intensity function can be defined as:

$$I(C, p) = \sum_{i=1}^{2} S(s_{\{\min, i\}}, p)$$

Here $s_{\{\min, i\}}$ are the closest sensors from each cluster $i = 1,2$ to point p.

4.3 Object Detection Probability

According to the random sensing schedule all the sensor have the same sensing range. Now if an object moves from left to right over $x-axis$ where we consider that each Voronoi edge is mapped on $x-axis$. Let the length of the Voronoi edge is L and an object moves from $(-L/2)\ to\ (L/2)$. Consider A is the active area and A can be defined as the rectangular area (shaded) in Fig-2 with length L and width of 2R. So the active area: $A = L * 2R$.

Observation 1: Let point p be the location of an object over a Voronoi edge and $\overline{P}$ be the detection probability of a closest sensor $s_{\min}$ to the point p. Point p has the common cluster intensity $I(C, p)$ due to $s_{\min}$. Thus,

$$\overline{P} = \frac{1}{A} \int_{-L/2}^{L/2} I(C, p)\, dx \quad \int_{-R}^{R} dy \cdot$$

Proof: To detect any object on a point p specifically a sensor should satisfy two conditions: $i)$ the sensor must be in active area and $ii)$ the sensor must be active when any object passes through the edge. The detection probability of the closest sensor to a point is totally depends on the length of the Voronoi edge and the intersection point of the sensors sensing range on that edge. As we consider that the Voronoi edge lies only along the $x-axis$ so the different random value of intersecting points should be in a range of $(-L/2)\ to\ (L/2)$. So, the derivation in the above observation can easily be justified by integrating the event space only in between $(-L/2)\ to\ (L/2)$ which in turn is the range of an active area A over $x-axis$. Here the total sample space is the active area A.

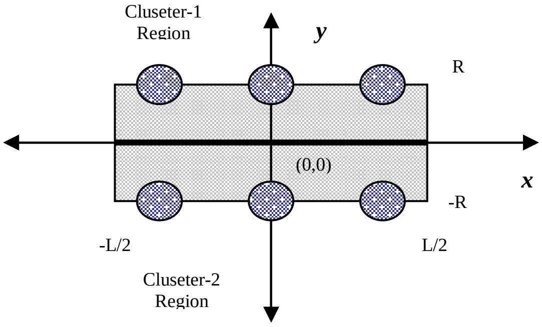


Fig. 2. A simple scenario for active area A.

Observation 2: For multiple sensors, in an active area since they are deployed and clustered randomly, the number of sensors in the active area follows a Poisson distribution. Thus the detection probability of randomly deployed sensors in an active area A is:

$$D(P) = 1 - e^{-\lambda \overline{P}}, \text{ Where } \lambda = [d(s_{\min}, p)] * A$$

Proof: Let k sensors have been deployed in an active area A and the probability of deploying k sensors is $P(k) = \frac{e^{-\lambda}.\lambda^k}{k!}$, $k = 0,1,2,......,\infty$. On the other hand, the probability of there exists k sensors in the active area and at least one of them can detect an object to a point over the Voronoi edge is $P(\det ection \wedge k) = \frac{e^{-\lambda}.\lambda^k}{k!}[1-(1-\overline{P})^k]$. When there exists no sensor in an active area that means $k=0$, then $P(0) = \frac{e^{-\lambda}.\lambda^0}{0!} = e^{-\lambda}$. As $\sum_{k=0}^{\infty} \frac{e^{-\lambda}.\lambda^k}{k!} = 1$, so we can write it in the way $\sum_{k=1}^{\infty} \frac{e^{-\lambda}.\lambda^k}{k!} = 1 - e^{-\lambda}$. Again $P(0) = \frac{e^{-\lambda}\lambda^0(1-\overline{P})}{0!} = e^{-\lambda}$, and $\sum_{k=0}^{\infty}\frac{e^{-\lambda}.\lambda^k(1-\overline{P})}{k!} = e^{-\lambda\overline{P}}$. Thus $D(p) = \sum_{k=1}^{\infty} P(\det ection \wedge k) = \sum_{k=1}^{\infty}\frac{e^{-\lambda}\lambda^k}{k!}[1-(1-\overline{P})^k] = (1-e^{-\lambda}) - (e^{-\lambda\overline{P}} - e^{\lambda}) = 1 - e^{-\lambda\overline{P}}$.

4.4 Exposure and Exposure Path

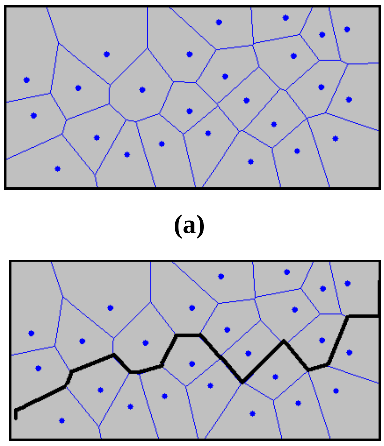
More formally exposure for a point or a path in a sensor network depends on the probability of detecting an object on that point by the sensors. Let $p_i \in (p_1, p_2, p_3, ...p_n)$ be a set of randomly generated points over a Voronoi edge. Thus the exposure of that edge can be defined as $Exposure = \sum_{p_i} D(P)$. Again an exposure path is the combination of several Voronoi edges, which connects a source and a destination point in a particular sensor region. Here each edge has the exposure value derived from the above exposure definition.

5. Minimum Exposure Path Estimation

This section describes our Voronoi diagram based estimation that solves the minimum exposure path identification problem. The estimation algorithm used here is computationally inexpensive and optimum. Because to detect any object over a point only the closest sensors intensity from each cluster are used for the proposed algorithm.

In order to maintain the low computation we made some assumptions for our proposed algorithm. Our proposed method assumes that the sensor nodes don't have the necessary information to compute shortest path locally. Sensor nodes should be location aware and location dependent. Moreover every sensor node stores topological and sensing information. Then each node receives and forwards that information to its neighbor node.

Detection probability on some random points over the Voronoi edges is determined by the exposure value of each edge. This exposure value is treated as the weight of each Voronoi edge of the diagram. The edge, which has least detection probability, is added to the shortest path list. The same process runs until it finds the destination point.



(a)

(b)

Fig. 3. (a) Voronoi diagram of clusters and **(b)** Minimum expo sure path.

Algorithm: Minimum Exposure Path (C, PI, PD)
1. **Generate** the Voronoi Diagram V for the cluster C
2. **for** each edge $e_i \in V$
   Derive end vertices $v_m \in v$ and $v_n \in v$
3. $Cost(v_m, v_n) = Exposure(e_i)$
4. v_{init} = closest vertex to P_I
5. v_{dest} = closest vertex to P_D
6. N' = $\{v_{init}\}$
7. **for** all vertices v
   if v adjacent to v_{init}
   then D(v) = Cost (v_{init}, v)
   else D(v) = ∞
8. **Loop**
   find w not in N' such that D(w) is minimum
   add w to N'
   update D(v) for all v adjacent to w and not in N'
   D(v) = min(D(v), D(w) + Cost (w,v))
   Until all v in N'
9. **MEP** = Path between v_{init} to v_{dest} with minimum $\sum D(v_i)$

The above algorithm for calculating the minimum exposure path follows the principle of Djikstra's Single-Source-Shortest path algorithm. In this algorithm clusters C and the source P_I and destination P_D are given as input. Accordingly the main target of this algorithm is to generate the minimum exposure path MEP. First part [line 1-5] of the algorithm is the initialization phase. In this phase the Voronoi diagram along with the weight of each Voronoi edge are derived and it has the complexity $O(n \log n)$. Here n is the number of sensor nodes deployed in the sensor field. Then in the rest of the part [line 6-9] the minimum exposure path is calculated with the help of single source shortest path calculation with a complexity of $O(v^2)$, where v is the number of end vertices of the edges in the total Voronoi diagram.

6. Numerical Simulations

A numerical simulation is performed which shows the performance of some of the aspects of the proposed method introduced in this paper. We consider a 2D plane plotted in Java. We have also considered some randomly generated points over the Voronoi edges. The sensors are deployed randomly where each sensor has the same sensing range. As the active area of a Voronoi edge totally lies on $x-axis$, so here we have performed the simulation for different length of an active area along with other parameters. Fig-4 presents the detection probability variation or exposure variation for different number of sensors. Exposure value always rises up when number of nodes increased and vice versa.

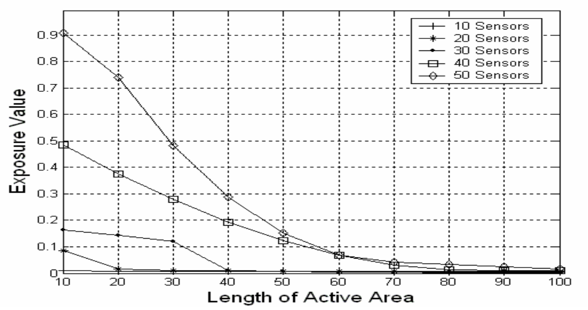


Fig. 4. Scenario for different exposure value in Active area

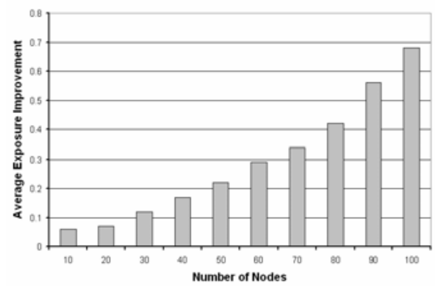


Fig. 5. Average Exposure Improvement vs. Number of Nodes

Fig-5 shows the average exposure improvement scenario for the proposed method while increasing the number of sensor nodes in the sensor field. In this analytical calculation we considered that the exposure path initially follows the closest point on the Voronoi edges from the source point P_I and finally it holds the closest point of Voronoi edge to the destination point P_D.

7. Conclusion

Now a day, Wireless sensor network become a key technology for surveillance systems. This paper addresses a unique idea regarding the exposure calculation in terms of probability of detecting any object. Here an inexpensive minimum exposure path calculation algorithm is proposed so that the quality and performance of network can be measured for further improvement. The numerical results indicate that the probability of detecting any object depends on the length of the monitored Voronoi edge as well as number of deployed sensors. The mathematical approach of exposure measurement could be implemented in a larger extent of wireless sensor network.

In case of advance level of research in wireless sensor coverage our probabilistic approach can play an important role to find out the weakness of a network. Thus steps can be taken accordingly. Though in the practical phenomena it is hard to implement the proposed approach still we hope our promote progression of this paper will contribute enormously.

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