Distributed In-network Processing of *k*-MaxRS in Wireless Sensor Networks

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Abstract: We address the problem of in-network processing of *k-Maximizing Range Sum* (*k*-MaxRS) queries in Wireless Sensor Networks (WSN). The traditional, Computational Geometry version of the MaxRS problem considers the setting in which, given a set of (possibly weighted) 2D points, the goal is to determine the optimal location for a given (axes-parallel) rectangle *R* to be placed so that the sum of the weights (or, a simple count) of the input points in *R*'s interior is maximized. In WSN, this corresponds to finding the location of region *R* such that the sum of the sensors' readings inside *R* is maximized. The *k*-MaxRS problem deals with maximizing the overall sum over *k* such rectangular regions. Since centralized processing – i.e., transmitting the raw readings and subsequently determining the *k*-MaxRS in a dedicated sink – incur communication overheads, we devised an efficient distributed algorithm for in-network computation of *k*-MaxRS. Our experimental observations show that the novel algorithm provides significant energy/communication savings when compared to the centralized approach.

1 INTRODUCTION

Wireless Sensor Networks (WSN) consist of hundreds, or even thousands of nodes capable of sensing particular set of phenomena, performing basic computations and, most importantly, communicating with each other (Akyildiz et al., 2002). They are the empowering technology for a wide range of applications including environmental monitoring, smart buildings and cities, safety and hazard detection, agriculture, medicine, military, traffic monitoring, etc. Due to the types of sensors used and/or various deployment constraints (e.g., harsh and inaccessible environments), re-charging nodes' batteries is not always feasible. Consequently, reducing the energy consumption is an ever-important topic in WSN, facilitating an extension of overall network's operational lifetime (Anastasi et al., 2009). While periodic sampling and transmission to a dedicated base-station may be applicable for certain applications, they may incur significant overhead in others – especially in event-based monitoring and tracking. To minimize communication overheads, various works have tackled coupling of routing schemes with aggregation and in-network query processing (Fasolo et al., 2007; Krishnamachari et al., 2002; Trigoni and Krishnamachari, 2012; Madden et al., 2005).

In this work, we take a first step towards providing a distributed, energy-efficient solution in WSN settings, to the problem known as (*k*-)MaxRS – which can be described as follows. Given a collection of *weighted objects O* and a rectangle *R* with fixed dimensions (i.e., $d_1 \times d_2$), the *Maximizing Range Sum* (MaxRS) query retrieves the location at which (the centroid of) *R* should be placed, so that the sum of the weights of the objects in its interior is maximized. In the context of WSNs, we can think of the set of sensor nodes as the set of weighted objects, where the "weights" are application dependent, e.g., mote readings (event monitoring), information gain (tracking an object), uniform (counting), etc. We note that MaxRS is rather different from the traditional *range* query in the sense that when processing a range query, the region is typically fixed and one is interested in properties that hold in its interior. Contrary to this, MaxRS determines *where* should a rectangle with given dimensions be placed, so that some "interesting" properties in its interior are maximized (modulo all the other possible placements). An instance of the MaxRS in WSN is shown in Figure 1(a), assuming

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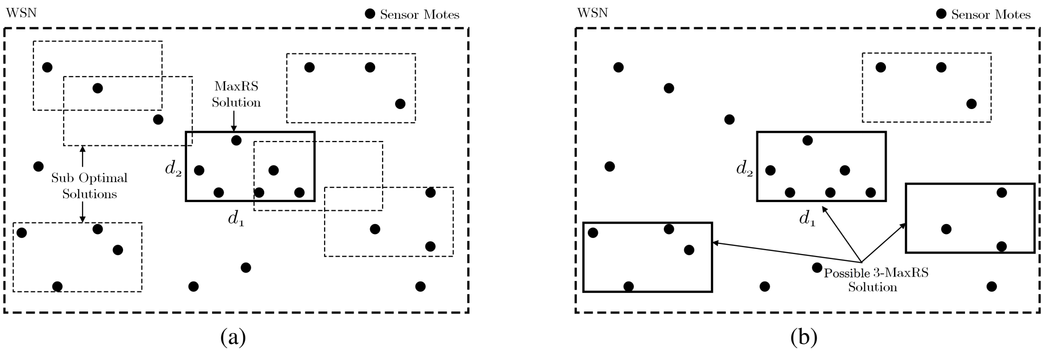


Figure 1: An example of (a) MaxRS and (b) k-MaxRS problem in WSN.

that the weights of all the sensor nodes are uniform – i.e., the "counting" variant.

Consider the following query:

Q1: *"Where should we place k surveillance devices (e.g., cameras, checkpoints, etc.) with a fixed-size coverage region in a forest such that their cumulative monitoring of forest-fire vulnerable regions (i.e., regions where temperature and light sensor readings are higher) is maximized?"*.

It is not hard to adapt **Q1** to other applications in which a simultaneous detection of top-k "popular" regions ($k \geq 2$) may be of interest. Such examples are: discerning k herds of tracked animals (e.g., gazelles) with largest density; aiding transportation system management by identifying k regions of the city with heaviest traffic; detecting congestions/hotspots in WSN by setting a node's current incoming/outgoing network traffic as its weight. One can also readily extrapolate to various collaborative scenarios – e.g., guiding drones towards regions where certain phenomenon has the largest weighted sum. To the best of our knowledge, the existing solutions (Hussain et al., 2015) to MaxRS queries in WSN can only be applied to retrieve an optimal location for a *single* rectangle R, whereas **Q1** is an instance of the k-MaxRS variant – which we tackle in this work.

The respective k-MaxRS query finds the placement-locations for k rectangles such that the weighted sums of all the objects in the (union of the) interiors of each of R placed at those locations are optimal. An example-solution of the k-MaxRS query in WSN for uniformly weighted nodes is illustrated in Figure 1(b) (k=3). Although the MaxRS problem has been addressed by both computational geometry and spatial databases communities (Choi et al., 2012; Choi et al., 2014; Imai and Asano, 1983; Nandy and Bhattacharya, 1995), to the best of our knowledge, there has been no solution considering k optimal placements in WSN settings. As mentioned, in WSNs it is paramount to have energy-efficient query processing, for which in-network aggregation of partial results is often the approach of choice (Fasolo et al., 2007; Krishnamachari et al., 2002). Another challenge in this scenario is that the weights (i.e., sensor readings, information gain, etc.) of the sensor nodes may change with time, although their locations are fixed.

The main contribution of this paper can be summarized as follows:

- We provide an efficient in-network distributed algorithm to compute k-MaxRS via a hierarchy of clusters.
- We provide effective data-sharing schemes among the cluster-heads (also called principals).
- We provide experimental observations quantifying the benefits of the proposed approach.

The rest of the paper is organized as follows: Section 2, introduces the necessary technical background and presents the formal description of the k-MaxRS problem. In Section 3, we discuss in details the possible centralized approaches and the different components of our distributed solutions. Section 4 presents the quantitative observations of the benefits of our approaches and Section 5 positions this work with respect to the related literature. We conclude the paper and outline directions for future work in Section 6.

2 PRELIMINARIES

We now introduce the basic notation, followed with an overview of the MaxRS problem and formal definition of the k-MaxRS query in WSN. We also briefly describe the existing solutions for the MaxRS problem to better motivate the algorithms and implementations proposed in this paper.

We assume a WSN covering an area $A_{WSN} = l \times w$ and consisting of n nodes, i.e., $WSN = \{sn_1, sn_2, \ldots, sn_n\}$, where each sn_i is equipped with whatever sensors are appropriate for the phenomena of interest for a given application. In addition, we also assume that the WSN is dense enough to ensure a coverage (i.e., every location in A_{WNS} is within the sensing range of at least one node) and connectivity (i.e., every two nodes sn_i and sn_j can communicate with each other either directly or via multiple hops).

MaxRS: Let $C(p,R)$ denote the region covered by R centered at a particular point p. We have:

Definition 1. (MaxRS) *Given a set of n points $O = \{o_1, o_2, \dots o_n\}$, and each o_i associated with a weight w_i, the MaxRS query retrieves a position p within the given space for an isothetic rectangle R of size $d_1 \times d_2$ such that $\sum_{\{o_i \in O \cap C(p,R)\}} w_i$ is maximal.*

In case of ties, one position is selected arbitrarily as the MaxRS solution. Without loss of generality, we assume that the set of points/objects $O = \{o_1, o_2, \dots, o_n\}$ coincides with the set of nodes in the $WSN = \{sn_1, sn_2, \dots, sn_n\}$. The weight(s) associated with a sensor node can be determined based on the various readings, as needed by a specific application.

***k*-MaxRS:** Let $Interior(p,R,O)$ denote a function that returns the subset of objects from O contained within R, when the centroid of R is placed at a given point p.

Definition 2. (*k*-MaxRS) *Given a set of n points $O = \{o_1, o_2, \dots o_n\}$, each o_i associated with a weight w_i, and an integer $k \geq 2$, the k-MaxRS problem finds a set of locations $P = \{p_1, p_2, \dots p_k\}$ for the centroids of k isothetic rectangles R_1, $R_2, \dots$, R_k, each of size $d_1 \times d_2$ such that:*

1. *For each $p_i \in P$, $\sum_{\{o_j \in O \cap C(p_i,R_i)\}} w_j \geq \sum_{\{o_j \in O \cap C(p',R_i)\}} w_j$, $\forall p' \notin P$*
2. *$Interior(p_i,R,O) \cap Interior(p_j,R,O) = \emptyset$, $\forall p_i, p_j \in P$ and $p_i \neq p_j$*

The second condition of the definition ensures that there are no overlapping objects between any two top-*k* solutions of the *k*-MaxRS problem. We note that, just like in the case of MaxRS, there can also be multiple possible solutions for the *k*-MaxRS problem as shown in Figure 1(b) – another rectangle (dashed) can also be taken as part of the solution, in place of the bottom right one.

In-memory MaxRS Solution: To compute MaxRS for static objects with fixed weights, the problem is initially transformed into a “dual” *rectangle intersection problem* as follows (cf. (Nandy and Bhattacharya, 1995)). For simplicity, let us consider the counting variant of the MaxRS problem here. We first draw a rectangle of size $d_1 \times d_2$ centered at each of the objects in O. R covers o_i if and only if its center is in the interior of the *dual rectangle* of o_i. Thus a rectangle covering the maximum number of objects can be centered at any location within the maximum intersecting region of the dual rectangles. Using the findings of (Imai and Asano, 1983) and this transformation, (Nandy and Bhattacharya, 1995) provided an in-memory algorithm to solve the MaxRS problem in $O(n \log n)$ time. Considering the top and bottom edges of the rectangles as horizontal intervals, an *interval tree* – i.e., a binary tree on the intervals – is constructed, and subsequently a horizontal line is swept in a bottom-up manner. The algorithm maintains the *count* for each interval currently residing in the tree, where the *count* of an interval represents the number (or, the sum of weights) of overlapping rectangles within that interval. An interval with the maximum count during the whole sweeping process is the final solution.

3 PROCESSING *k*-MaxRS

We start this section with presenting two techniques to compute *k*-MaxRS in centralized settings: Object Removal Method (ORM) and List Method (LM). This is followed by the details of our proposed in-network algorithm for processing *k*-MaxRS that employs clustering, routing, and data-aggregation schemes.

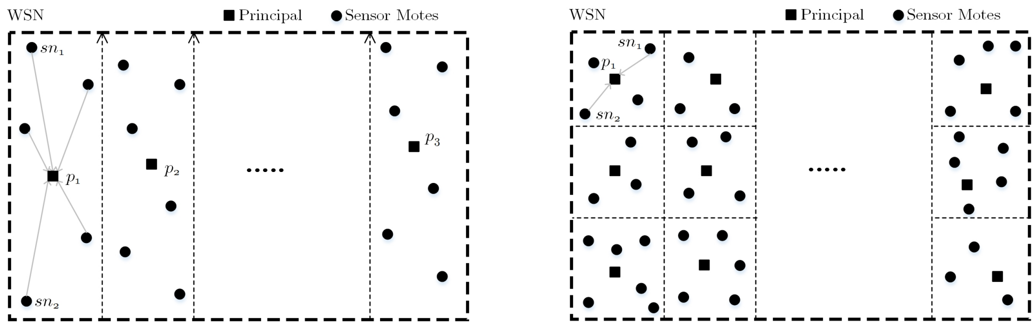
3.1 Centralized Algorithms for *k*-MaxRS Processing

Objects Removal Method (ORM): The simple/intuitive idea behind this method is to use the MaxRS algorithm (Nandy and Bhattacharya, 1995) iteratively k times, as follows:

1. Execute the MaxRS procedure over the current set of objects, and retrieve the optimal location p for the query rectangle R.
2. Set the current set of objects to be $O - Interior(p,R)$.

After performing steps (1) and (2) k times and storing the solution from each iteration, we can obtain the answer-set to the *k*-MaxRS problem. Since MaxRS solution in (Nandy and Bhattacharya, 1995) takes $O(n \log n)$ time, the overall complexity of this technique is $O(kn \log n)$.

List Method (LM): This is a modified plane-sweep procedure based on (Nandy and Bhattacharya, 1995), where each internal node v of the interval tree maintains a field *target* – pointing to the interval with maximum count within the sub-tree rooted at v itself. To compute *k*-MaxRS, we maintain an answer-set of size k during the whole plane-sweep procedure. Whenever



(a) (b)

Figure 2: Different types of clustering schemes: (a) vertical slabs (b) $m \times n$ grids.

a new interval (a.k.a. window) is added to or removed from the tree, the target pointers of the affected internal nodes are updated accordingly. When an interval is inserted/deleted – only a subset of the interval tree is affected (all the nodes in path F_{IN}, F_L, and F_R – cf. (Nandy and Bhattacharya, 1995)). Thus, after insertion/deletion of an interval, the answer-set is updated by comparing with the target values of these affected nodes only. All such nodes can be traversed in $O(\log n)$ time, and $O(k)$ time is needed to update the answer-set for a changed target value. The processing time of a single plane-sweep event is thus $O(k \log n)$. As there are $O(n)$ events (2 for each rectangles, i.e., top and bottom edges), the time-complexity of this algorithm is $O(kn \log n)$.

Additionally, suppose two intervals I_i and I_j overlap, and $count(I_i) \geq count(I_j)$. In such cases, I_j would be discarded from the answer-set even if its count puts it in the top-k (due to violation of condition 2 of Definition 2). Note that, we maintain a hash-table, *dict*, where a *key* is an interval and corresponding *value* is a set of intervals that have been discarded from consideration due to overlapping with the *key* interval. If we consider the previous example, one of the <*key*, *value*> pair of the *dict* table will be $< I_i, \{I_j\} >$. This aids us in retrieving the interval I_j back, if later I_i itself is discarded for overlapping with another interval of higher count. As we use a hash-table (i.e., amortized access cost of $O(1)$), this does not affect the overall time-complexity.

Extension & Comparison

Both LM and ORM can be used to process k-MaxRS in WSN in a naïve manner, i.e., all the sensed values (or, current weights) are transmitted to the sink (directly or via multi-hop transmission), where the sink can use either of the two techniques to compute current MaxRS solution. ORM has two significant pitfalls:

- Firstly, it can still produce answer-sets violating condition 2 of Definition 2.
- Secondly, and more importantly, for some degenerated cases, it can produce sub-optimal k-MaxRS answer-sets.

Regardless of these, though, any centralized processing which takes place in a dedicated sink incurs a significant communication overhead.

3.2 Distributed Algorithm for k-MaxRS Processing

The basic idea behind our proposed in-network processing is: (1) Divide the whole network into subnetworks (clusters); (2) Localize the computation process within the clusters; and (3) Execute a data aggregation scheme between neighboring clusters – the details of which we present in the sequel.

Geographical Clustering

In (Choi et al., 2014), a distributed solution to the MaxRS problem was devised for large spatial databases, extending the idea of the in-memory algorithms to the settings in which data resides on a secondary storage. The work aimed at reducing the number of I/O's – and the main idea was centered around dividing the space into m vertical slabs along the X-dimension, until the number of rectangles in a slab can fit in the main memory. For each slab, a variant of the in-memory sweep-line algorithm is performed and the results are saved in a *slab file*. Finally, all the local *slab files* are merged into one solution *slab file*. Although the idea works well in spatial databases context, its straightforward extension is not well-suited in case of WSN. A vertical subdivision of a sensor network (similar to (Choi et al., 2014)) is presented in Figure 2(a). Each such slab (cluster) is assigned a *local principal* (similar to cluster-heads), which is in charge of gathering the raw data (i.e., weights) from all the nodes in the interior of its own slab. As the sensor field can be of a large size in both length and width, some sensor nodes might still be far from the local principal which will result in inefficient network route to that principal – e.g., path to p_1 from nodes sn_1 and sn_2 in Figure 2(a).

To avoid such cases, we propose to split the zone of interest into $m \times n$ grid of equal-sized cells. Each cell will be assigned a local principal, and the value of m and n can be set based on some desired criteria, e.g., the average number of sensors within a cell, a limit on the number of hops when communicating with the principal, etc. The benefit of this space-clustering method is shown in Figure 2(b), as now we can control the communication distance between nodes and their local principal. Other similar space-partitioning schemes (e.g., K-d tree (Mohamed et al., 2013)) can be considered, but the important observation is that subsequently the principals are organized in a hierarchical (tree-like) digraph – *principal graph* – rooted in a dedicated sink (more details in the following sections). The impact of this geographic clustering and hierarchical digraph for principals is two-fold: (1) It helps in localizing the processing as each principal can compute k-MaxRS for its own cell; and (2) It enables a distributed solution even for the case when some of the rectangles from the k-MaxRS answer-set spans across ≥ 2 cells.

Base Method

For in-network processing, LM is more suited than ORM, because ORM would need to execute MaxRS k times iteratively, and doing the in-network processing k times among the clusters would still incur significant communication overhead – possibly even exceeding the centralized approach for a large k. On the other hand, the sweep-line procedure is performed only once for LM, i.e., a single in-network processing cycle can retrieve the k-MaxRS answer-set. Thus in our distributed technique, each local principal in a given cluster uses LM to compute the answer-set in that cluster.

Routing & Data Aggregation

One way to divide routing protocols in WSN is into two categories: hierarchical and "flat". In this work, we employ a hierarchical digraph-based routing protocol among the principals, and data propagation and aggregation is achieved by relaying messages from predecessors to successors. As a result, the local principals form a digraph, denoted *principal graph*, in our distributed scheme. Before going into the details about principal graph, we define the term *safe region (SR)* for a cell as the geographical region within which all the local processing of k-MaxRS for that cell is final. In other words, no k-MaxRS solution can span outside the safe region. The safe region of a cell for a given query rectangle R of size $d_1 \times d_2$ is illustrated in Figure 3, and we observe that the information of all the sensor nodes $\notin SR$ (indicated in red in Figure 3) must be shared with the neighboring cells when determining the answer.

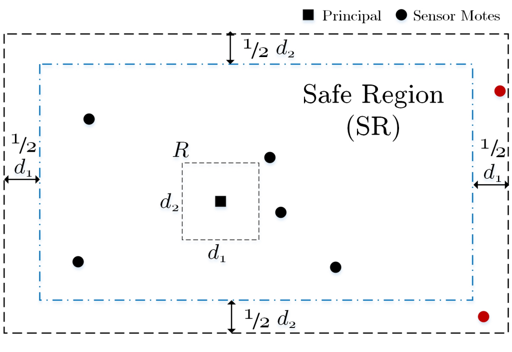


Figure 3: The safe region within a cell.

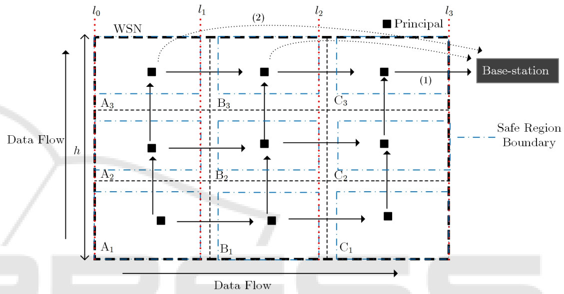


Figure 4: The principal graph and data aggregation to the sink.

A cell can have as many as 8 neighbors (e.g., B_2 in Figure 4), and sharing data with all of them may not be efficient. Instead, we use the principal graph as shown in Figure 4. For a principal p_M of the cell M (under a suitable cell-addressing scheme), we will use p_M^p and p_M^s to denote the set of its predecessors and successors in the principal graph respectively. The hierarchical digraph is formed by creating directed edges from each principal to the principals of the cells immediately up ("north") and right ("west") directions (if exists). Thus, a principal will have at most two successors and two predecessors in the graph, e.g., for A_2 in Figure 4 – $p_{A_2}^p$={A_1} and $p_{A_2}^s$={A_3, B_2}. Successors are considered to be in higher level in the hierarchy than their predecessors, and the sink is kept in the highest level of the hierarchy (i.e., has no successors). In this scheme, each principal p_M shares its data with only at most two neighbors – its successors, i.e., p_M^s. Thus, p_{A_2} in Figure 4 will share its data with only p_{A_3} and p_{B_2}. A principal shares the following data with its successors: (1) local k-MaxRS answer-set; (2) the *dict* hash-table; and (3) the data of the nodes in the unsafe region. In this setting, the principal of cell A_3 has the valid k-MaxRS answer-set for the region of the network between l_0 and l_1 (cf. Figure 4). Similarly, the principal of cell B_3 has valid answers for the region l_1 and l_2, and so on. Finally, the sub-solutions can be merged in two ways: (1) In the top-right cell (i.e., C_3 in Figure 4); and (2) In the base-station (using dotted connections in Figure 4). To eradicate any dependency on the base-station, we employ the former method.

Algorithms

There are two types of nodes (entities) in our distributed scheme: (1) Sensing nodes; and (2) Local principals. The behavior of a sensing node in *k*-MaxRS processing is rather simple:

1. After a pre-determined (fixed) period, collect/update its own application-specific weights (e.g., sensed phenomena values, network traffic, consumed energy, etc.).
2. If there is any update of the weight, send the new value to the local principal.

The behavior of local principals is specified in Algorithm 1, which we now explain. Initially a principal receives the cell-boundary information, along with two other values – (1) the dimensions of the range *R*; and (2) λ – the re-evaluation frequency – directly from the base-station. Using the received parameters, the principal establishes connection with the relevant nodes, i.e., all the nodes in its cell, and the principals corresponding to its p^p and p^s neighbors (cf. Lines 1-2). *SR* is then computed and the principal detects/marks the nodes in its unsafe region (Line 3). Lines 5-17 are executed until new parameters are received from the base-station. In Lines 5-6, the principal waits to receive relevant information from the sensing nodes (i.e., the weights of their measurements), and p^p. At each time-interval λ, Lines 8-16 are processed. After adding the information of nodes in the neighboring predecessor principals' unsafe regions, a principal performs the LM method to compute its own local *k*-MaxRS answer-set (cf. Lines 8-9). Then it combines the *dict* tables from the neighbors with its own in Line 10. In Line 11, *Compare* is a method which takes all the local solutions – a cell's computed answer-set and from p^p – and retrieves the top-*k* non overlapping positions using the merged *dict* hash-table. Finally, if the principal is the immediate predecessor of the sink, it sends the final solution only directly to the sink. Otherwise, relevant information is sent to p^s.

We re-iterate that there is the user-defined parameter λ (a.k.a. sampling rate) specifying the "freshness" of the answer-set, i.e., the frequency of re-evaluating *k*-MaxRS. What this entails is if *k*-MaxRS is computed at time *t*, only the nodes within the answer-set rectangles are kept awoken between *t* and $t+\lambda$, thereby limiting the awareness of the fluctuation of the weights corresponding to the monitored phenomenon. At time $t+\lambda$, all nodes are awakened, and subsequently *k*-MaxRS is re-computed with updated weights throughout the entire network and the states (awake, or idle) of the nodes are changed accordingly.

Algorithm 1: *k*-MaxRS-Principal (R, λ, C).

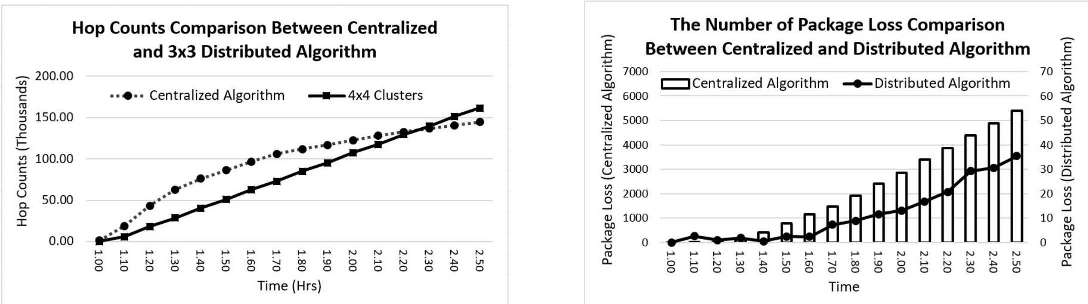
Require: A rectangle R of size $d_1 \times d_2$, a time-interval λ, and a principal's own cell C
Ensure: Sending data to be shared with p^s, or the final answer-set *kmaxrs* to the sink
1: Establish connection with all $sn_i \in WSN_C$
2: Establish connection with p^p and p^s
3: Compute safe region *SR* using *C* and *R*
4: **while** *Not Interrupted* **do**
5: Receive $(location, w_i)$ data from all $sn_i \in WSN_C$
6: Receive $(kmaxrs_i, dict_i, unsafe_i)$ from $p_i \in p^p$
7: **if** a time-interval ends after λ time **then**
8: Add $unsafe_i$ to WSN_C
9: $(kmaxrs, dict) \leftarrow LM(WSN_C, R)$
10: Merge *dict* and $dict_i$ from $p_i \in p^p$
11: *kmaxrs* $\leftarrow$ *Compare*(*kmaxrs*, $kmaxrs^p$, *dict*)
12: **if** p^s=$\{sink\}$ **then**
13: **return** *kmaxrs* to the sink
14: **else**
15: **return** $(kmaxrs, dict, unsafe)$ to p^s
16: **end if**
17: **end if**
18: **end while**

4 EXPERIMENTAL EVALUATION

We now describe our experimental observations regarding the benefits of the proposed approaches[1].

Tools and Setup: We conducted the experiments in an open-source WSN simulator, SIDnet-Swans (Ghica et al., 2008) – which has been used as an experimental tool in prior works (Trajcevski et al., 2011; Bai et al., 2011). The simulator is configured as follows: (1) 20 Kbps radio data rate on the MAC 802.15.4 protocol; (2) Shortest path geographical routing algorithm protocol (Banerjee et al., 2012) between nodes; (3) Utilization of Heart-Beat protocol (Li and Tan, 2007) to create the routing table in the MAC layer for each node within the first

[1] All the source codes and datasets for the experiments reported in this paper are publicly available at: http://www.eecs.northwestern.edu/˜pwa732



(a) (b)

Figure 5: (a) Hop count comparison, and (b) Amount of packet loss between centralized and distributed schemes.

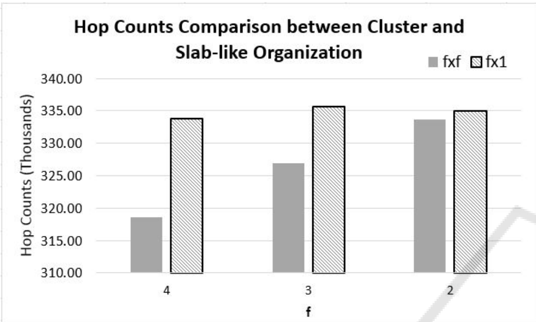


Figure 6: Hop count comparison between different distributed schemes.

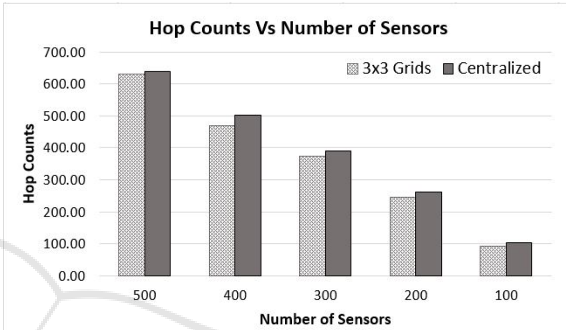


Figure 7: Performance of algorithms on various cardinality of objects.

hour when the simulation starts; (4) Communication range of 100 meters; (5) Power consumption model according to the TelosB mote's specifications; and (6) Initial capacity of a fully-charged battery of 25 mAh. Note that, a fully-charged sensor can run for 48 active-hours during simulation before running out of battery-charge. We used Java to implement the corresponding algorithms in SIDnet-Swans.

Default Settings: We set $|WSN|$=300, i.e., 300 homogeneous sensors over a 640×640 m^2 field. We used a rectangle of size 75×75 m^2 as query rectangle (R) throughout our experiments, with $k = 2$. We set sampling rate λ to 5 minutes, and default distributed clustering to 3×3 cells.

We used the following configurations: (1) Centralized – all nodes send data to the sink; and (2) Distributed – all sensing nodes send weights to local principals. Two types of sub-division are employed: (1) Grid-based; and (2) Vertical Slab-like. Unless indicated otherwise, we measure/report the raw hop counts of all the algorithms' run for 2 hours – assuming, as indicated above, the typical TelosB mote energy consumption per transmission.

Results: Figure 5 shows the hop counts of both the centralized and distributed processing in the default settings, running for 1.5 hours. As illustrated, the number of hop counts of the distributed technique is significantly smaller than the centralized one. As time increases, the difference in hop count increases as well, e.g., the difference is around 7500 at $t = 1.1$ hours while it steadily grows to be close to 14000 at 1.5 hours mark. Note that, the raw hop count is less in the first hour for both schemes as most of that time is spent in setting up the network.

The performance comparison of the vertical slab-like and grid-based formation is shown in Figure 6. We perform the experiments in three different sizes for both formations – 2×1, 3×1, 4×1 for vertical slabs, and 2×2, 3×3, 4×4 for grid-based cells – and we note that in the figure itself, the legend lists them as "$f \times 1$" and "$f \times f$" configurations, with the different values for f indicated on the x-axis. As shown, in all the cases, grid-based clustering scheme outperforms slab-like subdivision technique. Section 3.2.

The effect of the varying number of clusters in distributed algorithms is shown in Figure 6. For both grid-based cells and vertical slabs, hop count significantly decreases as we increase the number of clusters. In case of grid-based cells, if we raise the count of cells from 4 to 9, the hop count decreases by more than 40000, while it further plummets by around 22000 when we use 4×4 (16) grid cells. Note that complementary to this trend, when forming too many clusters, there are added hindrances of increased num-

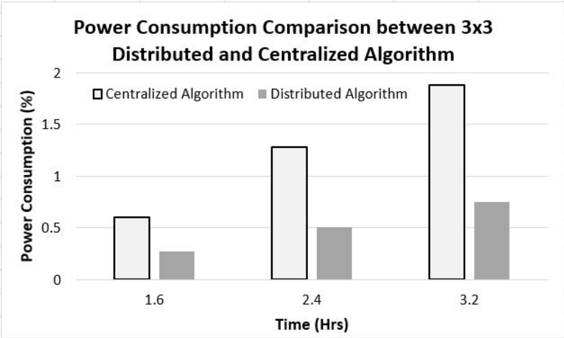


Figure 8: Average energy consumption comparison between distributed and centralized algorithm.

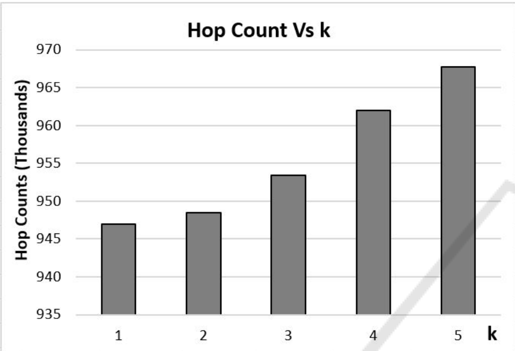


Figure 9: Performance *k*-MaxRS using different *k* values.

ber of resource-demanding principal sensors and the relative decrease in the area of safe-regions for clusters.

The effect of varying the size of WSN is illustrated in Figure 7. As expected, the rise in the number of nodes in WSN increases the hop count of both the centralized and distributed algorithm. A noteworthy observation is that distributed technique (3×3) performs better than the centralized scheme in all the cases.

Figure 8 demonstrates an important feature of our distributed scheme – overall less energy consumption, which in turn increases overall network lifetime. We ran both the distributed and centralized approach in the default settings for 3.2 hours and computed average energy consumption over all the nodes in the network. As can be seen in Figure 8, energy consumption is at least 2-3 times more in centralized approach than the distributed one. Also, as time increases, this difference increases as well, indicating the efficacy of our proposed algorithm in the long run.

This experiment measured the number of hop counts when the k values are varied at the end of the second hour. Figure 9 shows that hop counts increase for larger k since, when k is high, our algorithm needs to send more possible solutions to the neighbor clusters, resulting in more hop counts.

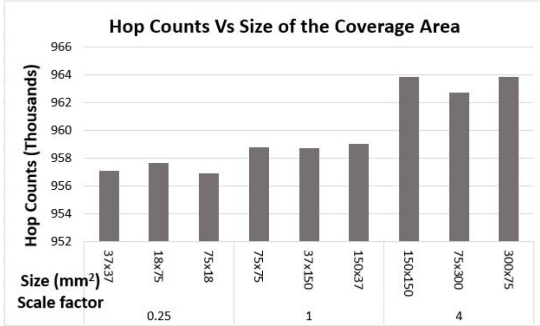


Figure 10: Performance *k*-MaxRS using different *k* values.

We did another experiment by changing the shapes and sizes of the query region with the scale factor of 4, and we measured the hop counts of different query regions. Figure 10 measures the number of hop counts once the shapes and size of the query region are changed – confirming that the larger query region is, more hop counts are needed. For larger query region, each principle node has to transmit to the neighbor clusters more data of the objects within the area outside its cluster, extended by the size of the specified query region. The larger extended area would include more objects from other neighbor clusters, and again each principle node has to send more data/messages to other neighbor-clusters.

Our last experiments measured the variation of accuracy of k-kMaxRS with the sampling rates (λ), reported for two different sampling values: 1 and 5 minutes. We recorded the locations and weighted sums of each MaxRS rectangle every minute, and compared those outputs with the one where k-MaxRS is calculated once every 5 minutes. We ran the experiments for 10 times and averaged the percentage of overlap of all k-MaxRSs – and we did the same for the weights (measured in the optimally-located rectangles). The results, shown in Figure 11 illustrate that the k-MaxRS at the lower sampling rate may induce significant errors in terms of keeping the sink up to date – both in terms of the locations of R as well as the values of the weighted sums. More specifically, the results show the percentage of overlap of the values between the once-in-5 minutes sampling vs. sampling every minute. The overlaps tend to reach 100% by the end which, in a sense, is expected since the phenomenon of interest is measured at $t = 5$ by both setups. We note that the difference in energy consumption was almost-linear – i.e., the sampling with $\lambda = 1$ consumed approximately 5 times more energy than the case of $\lambda = 5$. The investigation of balancing the trade-off between the (im)precision and residual energy (or overall lifetime) of the WSN, however, is beyond the scope of this work.

5 RELATED WORKS

The MaxRS and its variants were first tackled by the researchers from computational geometry, devising in-memory algorithms of $O(n \log n)$ time-complexity (Imai and Asano, 1983; Nandy and Bhattacharya, 1995). Motivated by applications from the class of Location-Based Services (e.g., best location for a new franchise store with a specified delivery range; most attractive place for a tourist with a restricted reachability), scalable solution for MaxRS in spatial databases were proposed (Choi et al., 2012; Choi et al., 2014). The distribution schemes proposed in (Choi et al., 2014) work nicely for secondary memory settings but, it appears that the vertical subdivision of space used in those works is not well-suited for WSN settings (cf. Section 3 and 4).

Recently, different variants of the MaxRS problem were investigated: – constraining locations of the objects to an underlying spatial network (Phan et al., 2014); – monitoring MaxRS over spatial data streams (Amagata and Hara, 2016); – rotating-MaxRS problem, i.e., allowing non axis-parallel rectangles (Chen et al., 2015). While interesting variants of the traditional MaxRS problem, these works did not consider the distributed processing aspects which are typical for WSN settings, nor the multiple (k) solutions.

A system implementing in-network solution to (a single, $k = 1$) MaxRS query in WSN was presented in (Hussain et al., 2015). We note that a similar philosophy of hybrid hierarchical clustering and routing scheme (although tree-based, not digraph-based) were used in (Avci et al., 014b), for different settings – i.e., detecting and tracking evolving shapes in WSN. Although there have been numerous works addressing energy conservation in WSN (Anastasi et al., 2009), to our knowledge, no energy-aware aggregation and routing approaches exist for the k-MaxRS problem in sensor networks.

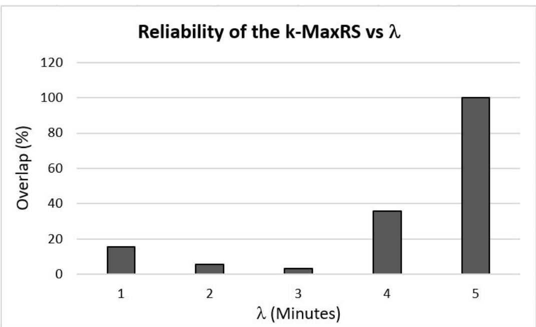


Figure 11: Performance k-MaxRS processing using different λ values.

6 SUMMARY & FUTURE DIRECTION

We presented an efficient distributed algorithm for processing k-MaxRS queries in WSNs. The unique nature of the k-MaxRS is that a collection of k fixed-size rectangles needs to be placed at distinct locations, in a manner that ensures that the sum of the respective (weighted) density/values in their interiors is maximized. We proposed a geographic clustering scheme where principal nodes (i.e., cluster heads) not only collect and aggregate data from their children, but also communicate with the siblings (i.e., other principals – predecessors and successors) in order to detect the answer to the k-MaxRS query as early in the hierarchy as possible, while reducing the overhead of communicating with all the possible neighbors.

To the best of our knowledge, k-MaxRS has not been addressed before in the context of WSNs and there are multiple extensions and variants to be investigated, some of which we plan to address in the near future. There are three distinct facets of the problem that we are currently focusing upon from complementary perspectives: (1) The incorporation of the (un)reliability of the links and transmission errors, along with more detailed consideration of different power-consumption models; (2) The investigation of the impact of the discrepancy of the nodes locations distribution; and (3) Dynamically adjusting the size of the query-rectangle and/or k based on trade-offs among different constraints (e.g., turnaround time, overall energy consumption, "freshness" of the data in the sink, etc.). In addition, we would like to investigate the incorporation of other kinds of dynamics-related contexts: from the impact of the different partitioning values (i.e., "m" and "n") and adaptive congestion management (Ren et al., 2011; Wan et al., 2003), through dynamic routing and aggregation structures (Fasolo et al., 2007), to incorporating mobile nodes/sink (Mohamed et al., 2013).

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