Privacy and Integrity Preserving Range Queries in Sensor Networks

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1. INTRODUCTION

The architecture of two-tiered sensor networks (illustrated in Fig. 1), where storage nodes serve as an intermediate tier between sensors and a sink for storing data and processing queries, has been widely adopted because of power and storage saving for sensors as well as the efficiency of query processing. However, a compromised storage node imposes significant threats. First, it may allow attackers to obtain sensitive data stored in the storage node. Second, it may return forged data for a query. Third, it may not return all data items that satisfy the query. Several privacy and integrity preserving protocols [1, 2] have been proposed to prevent attackers from gaining information from both sensor collected data and sink issued queries, and allows the sink to detect compromised storage nodes when they misbehave. However, the state-of-the-art protocol [1] has two main drawbacks: (1) it allows attackers to obtain a reasonable estimation on both sensor collected data and sink issued queries; (2) the power consumption and storage space for both sensors and storage nodes grow exponentially with the number of dimensions of collected data.

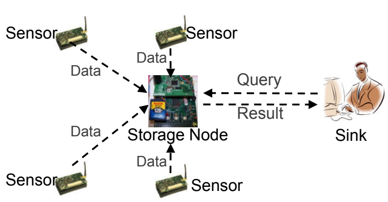


Figure 1: Architecture of two-tired sensor networks

In this paper, we propose SafeQ, a novel privacy and integrity preserving protocol for two-tiered sensor networks. To preserve privacy, SafeQ encodes both data and queries such that a storage node can correctly process encoded queries over encoded data without knowing their values. To preserve integrity, we propose the neighborhood chaining technique that allows a sink to verify whether the query result contains exactly the data items that satisfy the query. We also propose an optimization technique using Bloom filters to significantly reduce communication cost between sensors and storage nodes. Furthermore, we propose a solution to adapt SafeQ for event-driven sensor networks, where a sensor submits data when a certain event happens. Comparing with the state-of-the-art, SafeQ not only prevents attackers from knowing both sensor collected data and sink issued queries, but also delivers orders of magnitude better performance on both power consumption and storage space for multi-dimensional data.

2. MODELS AND PROBLEM STATEMENT

2.1 System Model

We assume that all sensor nodes and storage nodes are loosely synchronized with the sink. With loosely synchronization, we divide time into fixed duration intervals and every sensor collects data once per *time interval*. From a starting time that all sensors and the sink agree upon, every n time intervals form a *time slot*. From the same starting time, after a sensor collects data for n times, it sends a message that contains a 3-tuple $(i, t, \{d_1, \cdots, d_n\})$, where i is the sensor ID and t is the sequence number of the time slot in which the n data items $\{d_1, \cdots, d_n\}$ are collected by sensor s_i. We address privacy and integrity preserving ranges queries for event-driven sensor networks, where a sensor only submits data to a storage node when a certain event happens, in Section 7. We further assume that the queries from the sink are range queries. A range query "finding all the data items, which are collected at time slot t and whose value is in the range $[a, b]$" is denoted as $\{t, [a, b]\}$. Note that the queries in most sensor network applications can be easily modeled as range queries.

2.2 Threat Model

We assume that sensors and the sink are trusted but the storage nodes are not. In a hostile environment, both sensors and storage nodes can be compromised. If a sensor is compromised, the subsequent collected data of the sensor will be known to attackers and the compromised sensor may send forged data to its closest storage node. It is extremely difficult to prevent such attacks without the use of tamper proof hardware. However, the data from one sensor constitute a small fraction of the collected data of the whole sensor network. Therefore, we mainly focus on the scenario where a storage node is compromised. Compromising a storage node can cause much greater damage to the sensor network than compromising a sensor. After a storage node is compromised, the large quantity of data stored on the node will be known to attackers and upon receiving a query from the sink, the compromised storage node may return a falsified result formed by including forged data or excluding legitimate data. Therefore, attackers are more motivated to compromise storage nodes.

3. PRIVACY FOR 1-DIMENSIONAL DATA

To preserve privacy, each sensor s_i encrypts data items $d_1,\cdots,d_n$ using its secret key k_i, denoted as $(d_1)_{k_i},\cdots,(d_n)_{k_i}$. Note that, k_i is a shared secret key with the sink. However, the key challenge is how a storage node processes encrypted queries over encrypted data without knowing their values. The idea of our solution is to convert sensor collected data and sink issued queries to prefixes, and then use prefix membership verification to check whether a data item satisfies a range query. To prevent a storage node from knowing the values of data items and range queries, sensors and the sink apply Hash Message Authentication Code (HMAC) to each prefix converted from the data items and range queries. For example, consider sensor collected data $\{1, 4, 5, 7, 9\}$ and a sink issued query [3,6] in Fig. 2. The sensor first converts the collected data to ranges [min,1], [1,4], $\cdots$, [9,max], where min and max denote the lower and upper bound for all possible data items, respectively. Second, the sensor converts each range $[d_j, d_{j+1}]$ to prefixes, denoted as $p([d_j, d_{j+1}])$, and then apply HMAC to each prefix in $p([d_j, d_{j+1}])$, denoted as $h_g(p([d_j, d_{j+1}]))$. Third, the sensor sends the result to a storage node. When the sink performs query [3,6], it first converts 3 and 6 to prefixes, denoted as $p(3)$ and $p(6)$, respectively, and then apply HMAC to each prefix in $p(3)$ and $p(6)$, denoted as $h_g(p(3))$ and $h_g(p(6))$, respectively. Upon receiving query $h_g(p(3))$ and $h_g(p(6))$ from the sink, the storage node checks which $h_g(p([d_j, d_{j+1}]))$ has common elements with $h_g(p(3))$ or $h_g(p(6))$. Based on prefix membership verification, if $h_g(p(a)) \cap h_g(p([d_j, d_{j+1}])) \neq \emptyset$, $a \in [d_j, d_{j+1}]$. Therefore, $h_g(p(3)) \cap h_g(p([1,4])) \neq \emptyset$ and $h_g(p(6)) \cap h_g(p([5,7])) \neq \emptyset$. Finally, the storage node finds that the query result of [3,6] includes two data items 4 and 5, and then sends $(4)_{k_i}$ and $(5)_{k_i}$ to the sink.

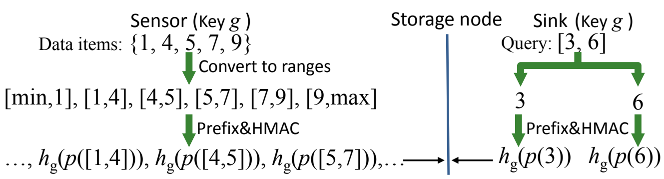


Figure 2: Privacy preserving scheme of SafeQ

4. INTEGRITY FOR 1-DIMENSIONAL DATA

To allow the sink to verify the integrity of a query result, the query response from a storage node to the sink consists of two parts: (1) the *query result* QR, which includes all the encrypted data items that satisfy the query; (2) the *verification object* VO, which includes information for the sink to verify the integrity of QR. We present *neighborhood chaining* technique to preserve integrity of a query result. The idea of this technique is that instead of encrypting each data item individually, a sensor encrypts each item with its left neighbor such that if a storage node excludes any data item that satisfies the query, the sink can detect it. Fig. 3 shows the neighborhood chain for the sensor collected data in Fig. 2. Here "|" denotes concatenation. For the range query [3,6], the query result QR is $\{(1|4)_{k_i}, (4|5)_{k_i}\}$ and the verification object VO is $\{(5|7)_{k_i}\}$. If a storage node excludes $(4|5)_{k_i}$ in QR, the sink can detect this error because the items in QR and VO do not form a neighborhood chain.

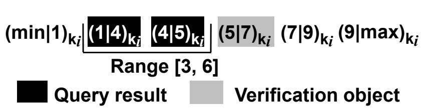


Figure 3: An example neighborhood chain

5. PRIVACY AND INTEGRITY FOR MULTI-DIMENSIONAL DATA

To preserve the privacy of multi-dimensional data, we apply our 1-dimensional privacy preserving techniques to each dimension of multi-dimensional data. For example, sensor s_i collects 5 two-dimensional data items (1,11), (3,5), (6,8), (7,1) and (9,4), it will apply the 1-dimensional privacy preserving techniques to the first dimensional values $\{1, 3, 6, 7, 9\}$ and the second dimensional values $\{1, 4, 5, 8, 11\}$. Given a range query ([2,6],[3,8]), the query result QR^1 for the sub-query [2,6] is the encrypted data items of (3,5),(6,8) and the query result QR^2 for the sub-query [3,8] is the encrypted data items of (9,4),(3,5),(6,8). Therefore the query result QR is the encrypted data items of (3,5),(6,8).

To preserve the integrity of multi-dimensional data, we build a multi-dimensional neighborhood chain. The idea is that for the value of each dimension in a data item, we find its left neighbor along each dimension and embed this information when we encrypt the item. Such neighborhood information is used by the sink for integrity verification. Considering 5 example 2-dimensional data items (1,11), (3,5), (6,8), (7,1), (9,4) with lower bound $(0, 0)$ and upper bound $(15, 15)$, the corresponding multi-dimensional neighborhood chain encrypted with key k_i is $(0|1, 9|11)_{k_i}$, $(1|3, 4|5)_{k_i}$, $(3|6, 5|8)_{k_i}$, $(6|7, 0|1)_{k_i}$, $(7|9, 1|4)_{k_i}$ and $(9|15, 11|15)_{k_i}$. Figure 4 illustrates this chain, where each black point denotes an item, the two grey points denote the lower and upper bounds, the solid arrows illustrate the chain along the X dimension, and the dashed arrows illustrate the chain along the Y dimension.

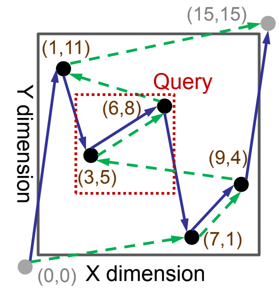


Figure 4: A 2-dimensional neighborhood chain

6. SAFEQ OPTIMIZATION

To reduce the communication cost between sensors and storage nodes, for n data items d_1, $\cdots$, d_n, we use a Bloom filter to represent $h_g(p([min, d_1]))$, $h_g(p([d_1, d_2]))$, $\cdots$, $h_g(p([d_{n-1}, d_n]))$, $h_g(p([d_n, max]))$. Thus, a sensor only needs to send the Bloom filter instead of the hashes to a storage node. The number of bits needed to represent the Bloom filter is much smaller than that needed to represent the hashes. Taking $h_g(p([4, 5]))$ and $h_g(p([5, 7]))$ in Fig. 2 as the example, we assume $h_g(p([4, 5]))$=$\{v_1\}$ and $h_g(p([5, 7]))$=$\{v_2, v_3\}$. $h_g(p([4, 5]))$ and $h_g(p([5, 7]))$ can be represented as the two arrays in Figure 5, where A is a bit array representing the Bloom filter and B is an array of pointers. Each pointer points to a list of indexes of ranges, *e.g.*, 2 is the index of [4,5] and 3 is the index of [5,7]. Note that, "-" denotes a null pointer. Although using Bloom filters may introduce false positives in the query result, *i.e.*, the data items that do not satisfy the query. We can control the false positive rate by adjusting Bloom filter parameters. For example, if each number in $h_g(p([d_j, d_{j+1}]))$ is 128-bit and the number of data items $n \geq 3$, to achieve reduction on the communication cost and the false positive rate of less than 1%, we can choose k ($4 \leq k < \frac{128}{1.44+2\lceil \log_2(n+1) \rceil}$) hash functions for the Bloom filter.

7. RANGE QUERIES IN EVENT-DRIVEN NETWORKS

So far we have assumed that at each time slot, a sensor sends to a storage node the data that it collected at that time slot. However, this assumption does not hold for event-driven networks, where a sensor only reports data to

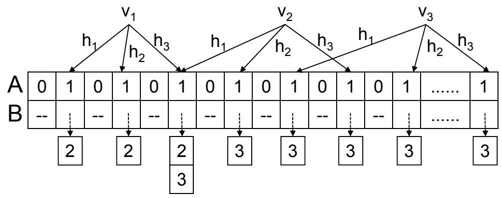


Figure 5: An example Bloom filter

a storage node when certain event happens. If we directly apply our solution here, then the sink cannot verify whether a sensor collected data at a time slot. We propose the *idle period* technique to address this challenge. The idea is that sensors report their idle period to the storage node when they submit data after an idle period or when the idle period is longer than a threshold. Storage nodes can use such idle period to prove to the sink that a sensor did not submit any data at any time slot in that idle period. Figure 6 illustrates two idle periods $[t_1, t_2]_{k_i}$ and $[t_3, t_4]_{k_i}$, where each unit in the time axis is a time slot, a grey unit denotes that s_i has data to submit, a blank unit denotes that s_i has no data to submit, and γ is the threshold.

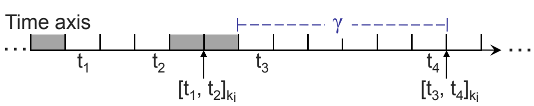


Figure 6: Example idle periods and data submissions

8. SECURITY&COMPLEXITY ANALYSIS

8.1 Privacy Analysis

In a SafeQ protected two-tiered sensor network, compromising a storage node does not allow the attacker to obtain the values of sensor collected data and sink issued queries. The correctness of this claim is based on the fact that the hash functions and encryption algorithms used in SafeQ are secure. In the submission protocol, a storage node only receives encrypted data items and the secure hash values of prefixes converted from the data items. Without knowing the keys used in the encryption and secure hashing, it is computationally infeasible to compute the actual values of sensor collected data and the corresponding prefixes. In the query protocol, a storage node only receives the secure hash values of prefixes converted from a range query. Without knowing the key used in the secure hashing, it is computationally infeasible to compute the actual values of sink issued queries.

8.2 Integrity Analysis

In a SafeQ protected two-tiered sensor network, the sink can detect whether the result of a query contains all the data items that satisfy the query and whether it contains forged data. The correctness of this claim is based on the following three properties that QR and VO should satisfy for a query. First, items in $QR \cup VO$ form a chain. Excluding any item in the middle or changing any item violates the chaining property. Second, the first item in $QR \cup VO$ contains the value of its left neighbor, which should be out of the range query on the smaller end. Third, the last item in $QR \cup VO$ contains the value of its right neighbor, which should be out of the range query on the larger end.

8.3 Complexity Analysis

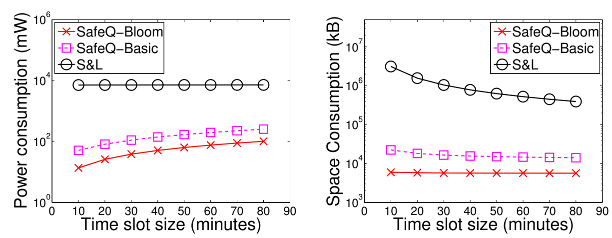
Given n z-dimensional data items that a sensor collects in a time slot, the computation cost, communication cost, and storage space of SafeQ are described in the following table. Note that the communication cost denotes the number of bytes sent for each submission or query, and the storage space denotes the number of bytes stored in a storage node for each submission.

	Computation	Communication	Space
Sensor	$O(zn)$ hash $O(n)$ encryption	$O(zn)$	–
Storage node	$O(z)$ hash	$O(zn)$	$O(zn)$
Sink	$O(z)$ hash	$O(z)$	–

Table 1: Complexity analysis of SafeQ

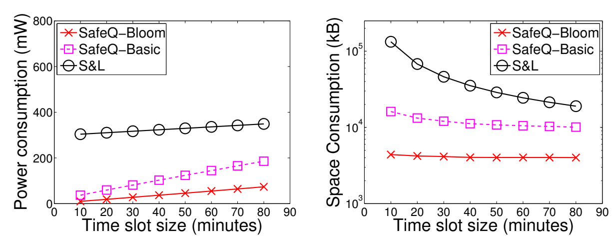
9. EXPERIMENTAL RESULTS

We implemented both SafeQ and the state-of-the-art (represented by S&L scheme) on a large real data set [3]. In comparison with S&L scheme, for 3-dimensional data, , our experimental results show that, SafeQ-Bloom consumes 184.9 times less power for sensors and 182.4 times less space for storage nodes; SafeQ-Basic consumes 59.2 times less power for sensors and 58.5 times less space for storage nodes. For 2-dimensional data, SafeQ-Bloom consumes 10.3 times less power for sensors and 10.2 times less space for storage nodes; SafeQ-Basic consumes 2.7 times less power for sensors and 2.7 times less space for storage nodes. Figures 7 and 8 shows the average power and space consumption for 3-dimensional and 2-dimensional data, respectively.



(a) Sensor: power consumption (b) Storage node: space consumption

Figure 7: Ave. power and space consumption for 3-dimensional data



(a) Sensor: power consumption (b) Storage node: space consumption

Figure 8: Ave. power and space consumption for 2-dimensional data

10. REFERENCES

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