

Secure Data Aggregation with False Temporal Pattern Identification for Wireless Sensor Networks

T. Abirami, M. Meenalochini, S. Anandamurugan

Abstract—Continuous aggregation is required in sensor applications to obtain the temporal variation information of aggregates. It helps the users to understand how the environment changes over time and track real time measurements for trend analysis. In the continuous aggregation, the attacker could manipulate a series of aggregation results through compromised nodes to fabricate false temporal variation patterns of the aggregates. Existing secure aggregation schemes conduct one individual verification for each aggregation result. Due to the high frequency and the long period of a continuous aggregation in every epoch, the false temporal variation pattern would incur a great communication cost. In this paper, we detect and verify a false temporal variations pattern by checking only a small part of aggregation results to reduce a verification cost. A sampling based approach is used to check the aggregation results and we also proposed a security mechanism to protect the sampling process.

Index Terms—Data aggregation, Sampling, Wireless Sensor Networks

I. INTRODUCTION

Wireless Sensor Networks (WSN) are widely used for environmental and security monitoring. Small wireless sensors have the capacity to sense, compute, store and transmit; it integrates with each other to form a network. In a WSN, the sensors monitor the immediate surroundings, and the data is transmitted to a well-equipped node called the Sink. Patterns in the data are analyzed offline, but this results in transmitting a large amount of data through the network leading to communication overhead. Protocols can reduce transmitted power in two ways. First where nodes can emit to short distances such as data sinks or cluster nodes. The cluster node can then send the data over a larger distance preserving the power of the smaller nodes. The second is by reducing the number of bits (amount of data) sent across the wireless network applications of wireless sensor networks (WSNs), the aggregations of sensed data, such as sum, average, and predicate count, are very important for the users to get

summarization information about the monitored area. Instead of collecting all sensor data and computing aggregation results at the base station (BS), in network aggregation allows sensor readings to be aggregated by intermediate nodes, which efficiently reduces the communication overhead.

II. METHODS AND IMPLEMENTATION

2.1 Representative point selection

The system initially identifies the representative points and performs the aggregation. The system performs continuous secure aggregation on every node by collecting a physical quantity of humidity and temperature from the surrounding environment and process the acquired data and transfer the collected data to a sink node or base station. Either in the on-demand verification or in the periodic verification, the BS selects some points from the series of aggregation results in the time window to be verified, and checks their correctness to detect any the modification of temporal variation patterns. Considering that the attacker can manipulate only a small number of aggregation results such as extreme points to change with the temporal variation pattern, it may be ineffective to check a set of randomly selected points to detect forged patterns because the selected points may not cover these manipulated points, which causes that the attack is not detected. To guarantee effective attack detection, the selected points should be able to capture the temporal variation pattern in the time window and these points as representative points and the epoch of a representative point as representative epoch.

2.2 Representative Point Selection (RPS) algorithm

We give the definition of representative point to formally characterize the requirement that is to capture the temporal pattern of the whole aggregation result series. Let $P = \{(e_i, Ag(e_i)) \mid 1 \leq i \leq p, e_1 = t < e_2 < \dots < e_{p-1} < e_p = t + l\}$ be a set of points in the time window $[t, t + l]$ where $Ag(e_i)$ is the aggregation result in epoch e_i . Let $F_p(*)$ be the piecewise linear function consisting of connected line segments, each of which is between point $(e_i, Ag(e_i))$ and $(e_{i+1}, Ag(e_{i+1}))$ for $1 \leq i \leq p - 1$.

The pseudocode of RPS algorithm is shown in Algorithm 1.

INPUT: $\langle \{(k, Agk) \mid t \leq k \leq t + l, p \rangle$ ($p \geq 2$)

OUTPUT: $\langle E[1, p], S \rangle$ // S is an array indexed from 1 and records $p-2$ number of epochs of representative points except t and $t + l$

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* Correspondence Author (s)

Dr. T. Abirami, Assistant Professor (SRG), Department of IT, Kongu Engineering College, Perundurai Tamil Nadu, India.

M. Meenalochini, PG Scholar, Department of IT, Kongu Engineering College, Perundurai, Tamil Nadu, India.

Dr. S. Anandamurugan, Assistant Professor (SRG), Department of IT, Kongu Engineering College, Perundurai, Tamil Nadu, India.

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1: // Entry E[i, j] records E(t; t + i, j)
2: // Entry s[i, j] records the representative epoch preceding t
  + i
3: for i ← 1 to l do
4:   for j ← 2 to p do
5:     if j = 2 then
6:       E[i, j] ← I(t; t + i); s[i, j] ← t
7:     else if j >= i + 1 then
8:       E[i, j] ← 0; s[i, j] ← t + i - 1
9:     else
10:      min ← ∞
11:      for k ← 2 to i - 1 do
12:        if min > E[k, j - 1] + I(t + k, t + i) then
13:          min ← E[k, j - 1] + I(t + k, t + i)
14:          s[i, j] ← t + k
15:      E[i, j] ← min
16:   end ← 1
17: for i ← 1 to p do
18:   end ← s[end; p - i + 1] - t
19:   if end > 0 then
20:     S [p - i - 1] ← end + t
21:   else
22:     break
23: return <E[l, p]; S >
    
```

2.3 Secure sampling

After the selection of representative points, the BS broadcasts a verification request, which includes the representative epochs, the sampling ratio and a nonce number nonce, to the WSN. Each sensor node has a unique identifier and shares a unique secret symmetric key with the base station. By pairwise key establishment schemes, each node shares a pairwise key with each of its direct neighbours and two-hop neighbours. A broadcast authentication protocol such as TESLA exists such that any node can authenticate a message from the base station. The WSNs have a short safe bootstrapping phase right after network deployment, during which attacker cannot successfully compromise any nodes.

2.4 Verifiable Random Sampling

In the verifiable random sampling, each node decides whether it is sampled by computing a cryptographically secure pseudorandom function h . h uniformly maps the input values into the range of $[0, 1]$ where nonce are nonce numbers that are disseminated within each aggregation query and verification request, respectively. In this way, whether a node is sampled is decided by the node individual key and two nonce numbers which are known by the BS. Since each time of verification different nonce is used, the nodes are randomly selected to be sampled for every verification. Also, a malicious node cannot decide to be sampled, since the BS can verify the legitimacy of sampled node. The actual number of samples returned by this sampling approach is random. Thus, the determination of sampling ratio q needs to provide a probabilistic guarantee to achieve the target sample size of at least m .

2.5 Local sample authentication

In the local sample authentication, each sampled node, say v , broadcasts its sample R_v to its neighbours to obtain authentication from its neighbours before sending R_v to the BS. Each neighbour u verifies the validity of R_v . If the verification is successful, u sends to v the message

authentication code of R_v computed by u 's key used for the authentication of v 's sample.

2.6 Local authentication key setup

To derive keys for the local sample authentication, each node u is loaded with a seedkey before deployment. The BS holds the seed keys of all nodes. During the safe bootstrapping phase, u discovers its one-hop neighbours and computes for each neighbour v . Since each authentication keys is bound with a neighbour pair, the attacker cannot use it to authenticate samples from malicious nodes except for the corresponding neighbouring node. The erasure of seed keys prevents the attacker from deriving all the authentication keys.

III. PERFORMANCE OF AGGREGATION VERIFICATION

To evaluate our aggregation verification scheme, we simulate a WSN of 100 nodes and the sensing readings of each node are synthesized to the sensor readings of a random node. We consider continuous average and count aggregation that counts the number of nodes whose temperature readings are greater than 25 in the time window. We simulate two attacks against the continuous average aggregation and predicate count aggregation in the time window.

In average aggregation, the attacker aims to delay the true time when the temperature increases. In the attack against count aggregation, the attacker aims to fabricate a false fluctuation of count value. Figures. 3.1 and 3.2 show both the real aggregation results and the forged one. Real aggregation have a rapid increase pattern between (20,50) for both average and count

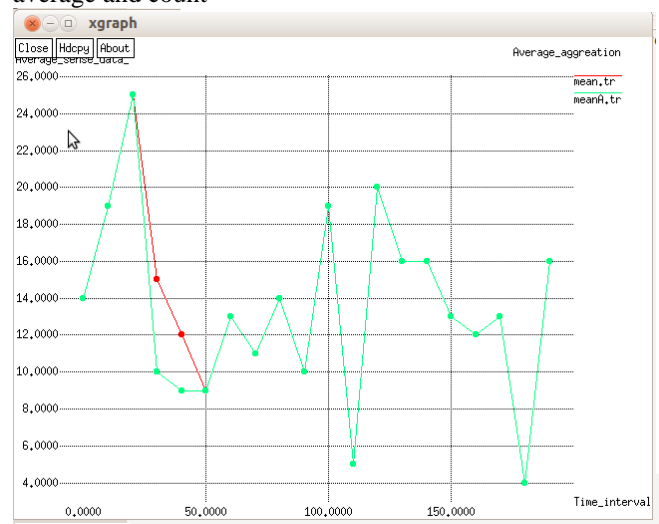


Figure 3.1: Continuous average aggregation under Attack



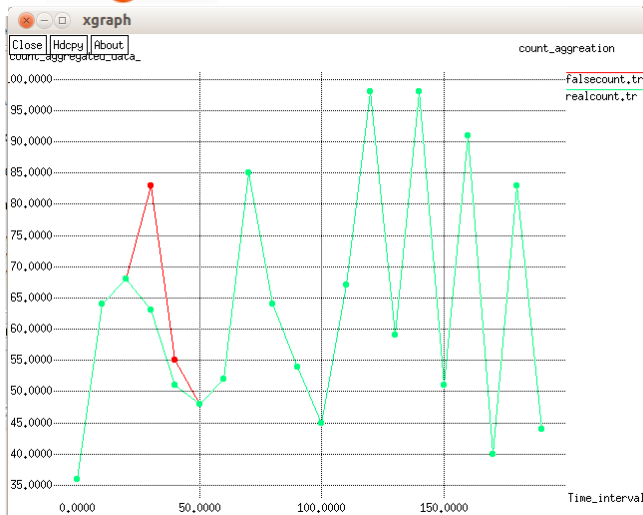


Figure3.2: Continuous count aggregation under attack

IV. CONCLUSION AND FUTURE WORK

In this paper we provide a distinct design issue for a verification scheme to protect the authenticity of the temporal variation patterns in the aggregation results. Compared with the existing secure aggregation schemes, the proposed scheme need to check only a small portion of aggregation results in a time window. The representative point selection algorithm is proposed to detain the temporal variation pattern. By exploiting the spatial correlation among the sensor readings in close proximity, a series of security mechanisms are also proposed to protect the sampling procedure. Future work includes studying further opportunities for load balancing and secure localization and addressing their threats.

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