

Research Article

Tracer: Taming Anomalous Events with CRFID Tags for Trajectory Management

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Mitigating anomalies are crucial for trajectory management in logistics and supply chain systems. Among variant devices for trace detection, computational radio frequency identification (CRFID) tags are promising to draw precise trajectory from the data reported by their accelerometers. However, full coverage of the processing flow using RFID readers is usually cost inefficient, sometimes impractical. In this paper, we propose to employ CRFID tags as tagging devices and develop a working system, Tracer, for precise trajectory detection. Instead of covering the entire processing area, Tracer only deploys RFID readers in essential regions to detect the mishandling, loss, and other abnormal states of items. We design a tree-indexed Markov chain framework, which leverages statistical methods to enable fine-grained and dynamic trajectory management. Results from a preliminary deployment on a real baggage handling system and trace-driven simulations demonstrate that Tracer is effective to detect the anomalous events with low cost and high accuracy.

1. Introduction

Trajectory management is of importance to manage and control objects for inventory, logistics, and supply chain applications (for simplicity, we term those applications as logistics systems in the rest of this paper). There is a notoriously difficult problem in those logistics systems: achieving fine-grained trajectory management to timely report anomalous events of objects. For example, the air transport industry (ATI) [1] reported 25.8 million mishandled bags globally in 2011, which tenders to a \$2.58 billion profit mitigation. In particular, about 53% cases occurred during the transfer processes, where the precise luggage tracking solution is lacking.

Prior works have adopted video cameras, cell phones, radio frequency identification (RFID) tags, and sensors to track movements of persons or objects for detecting whether the trajectories are in “normal” or “abnormal” situations. However, existing solutions have their intrinsic drawbacks. For example, video camera based monitoring [2] is cumbersome due to its fixed angle, inaccurate automatic video analysis, irregular activity detection, and high deployment

cost. GPS-based cell phones [3] are cost inefficient if being implemented to locate numerous objects in large-scale logistics systems. People also use wearable sensors for personal localization and motion capturing [4], but those sensors are easily susceptible to interferences from other wireless devices and environments. RFID based systems often adopt active [5, 6] or passive [7] tag arrays to track the objects. Active tags have a penalty of high cost and poor scalability when replacing battery in the real deployment [6, 7]. Being low-cost and power-free, passive RFID tags have been widely used in logistics systems. However, passive tags can only report their IDs to the reader and hence support the trajectory management in far coarse granularity. If one tagged bag falls out of the conveyor, while still staying in the interrogation region of the reader, as shown in Figure 1 (we define such a situation as an anomalous event in the following), it is difficult to timely detect such an anomalous event. The anomalous event may be reported after a long period, causing unacceptable delivery delay or even loss of the passenger luggage.

With the disadvantages of the previous works in mind, we are motivated to pursue a precise trajectory management

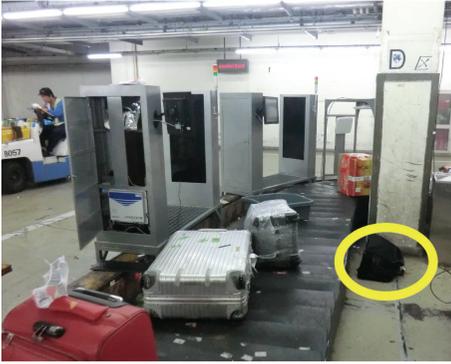


FIGURE 1: Anomalous events happen on a piece of luggage in logistics systems.

solution for logistics systems. Recently, the battery-free computational RFID (CRFID) tag [8, 9] is appealing to provide more context-aware information about objects. We propose to adopt CRFID tags in our trajectory management systems. Specifically, the collected vibration information from the 3D accelerometer allows CRFID tags to precisely and promptly detect the changes of objects trajectories, from which the legitimate trajectory pattern of objects can be derived.

To achieve this goal, we propose a CRFID based approach, Tracer, to obtain objects moving patterns for trajectory management. If the obtained patterns are anomalous, Tracer can alert the administrator to deal with the relevant objects in real time. Nevertheless, it is time consuming and costly to collect and process the accelerometer data from tags along the entire process flow in large-scale logistics systems. This becomes a key barrier that limits efficient processing and analysis of Tracer. We solve the problem twofold. First, instead of monitoring an object across the whole system, Tracer only interrogates the tags within the essential surveillance regions, such as the unloading point and junction areas between two conveyors (as shown in Figure 2). With the data collected from those essential segments, Tracer can reconstruct the trajectories of objects. Second, we adopt an efficient tree-indexed Markov chain framework into Tracer to detect the anomalous trajectories. The framework characterizes the legitimate patterns of objects based on the acceleration data. In particular, our framework takes the advantage of statistical methods for trajectory detection, which enables Tracer to be with relatively low deployment overhead and high accuracy of trajectory detection. The main contributions of our work are summarized as follows.

- (1) To the best of our knowledge, Tracer is among the first efforts to leverage CRFID devices for fine-grained trajectory management in real logistics applications.
- (2) Tracer adopts a tree-indexed Markov chain framework to reconstruct and monitor the trajectory patterns of objects. With the real accelerometer data as the input, this framework enables Tracer to react accurately and promptly upon anomalous events.

- (3) We perform extensive trace-driven simulations and preliminary implementation in a real baggage handling system in Beijing Airport. The result demonstrates the feasibility and effectiveness of Tracer.

The remainder of this paper is organized as follows. We provide an overview of related works in Section 2. In Section 3, we introduce backgrounds and fundamental observations that motivated this work. Section 4 elaborates the design of Tracer. In Section 5, we present the simulation results and evaluation. In Section 6, we conclude this paper and propose future direction.

2. Related Work

2.1. Motion and Body Trajectory. Motion capturing has been well studied in the body sensor networks and passive tag-based RFID systems, such as [4, 10–14]. The authors in [10] proposed a data processing technique that constructs motion transcripts from inertial sensors and identifies human movements by involving collaboration among the nodes into identification. Their work, however, targets on the distributed action recognition algorithm, while ignoring the detection of anomalous patterns that may affect the accuracy of movement classification. Klingbeil and Wark [4] proposed an indoor wireless sensor network (WSN) based approach for monitoring human motion and position. Their work requires prior knowledge about the environment, such as indoor map and seed nodes, to provide accurate position. Young et al. [13] presented an efficient distributed method which uses a model of the subject's body structure to estimate and correct for linear acceleration. The work in [15] proposed a WSN based mobile countersniper system to estimate the trajectory and range of snipers, as well as the caliber and type of their weapons. Existing works in the literature mainly focus on motion or body trajectory. They seldom adopt efficient frameworks to judge whether the data is accurate for motion capturing [11] and trajectory management [12, 15]. The work in [16] reported an RFID positioning system that leverages antenna arrays to localize tags under non-line-of-sight and rich multipath environments. In this paper, we adopt a tree-indexed Markov chain framework to detect whether the accelerometer data collected from CRFID tags is accurate, in order to yield a fine-grained trajectory management.

2.2. Vibration and Detection. Vibration is always an important factor for detecting various object behaviors in many applications [3, 5, 17–21]. In [17], the authors used sensor nodes to monitor hand-arm vibrations, which is important for monitoring health conditions of workers. Cell phones are used for movement detection [3] but usually with constraints imposed by the inaccuracy of commodity sensors and the limited battery power. For achieving efficient trajectory detection, the authors in [18] provided a mobility estimation and prediction for GSM networks. Their system is similar to the wireless ad hoc structure. Active RFID techniques [5, 7] are also adopted for activity monitoring using frequent trajectory pattern mining [5]. But the scalability problem [7] is a challenging issue due to the predeployment of tag array

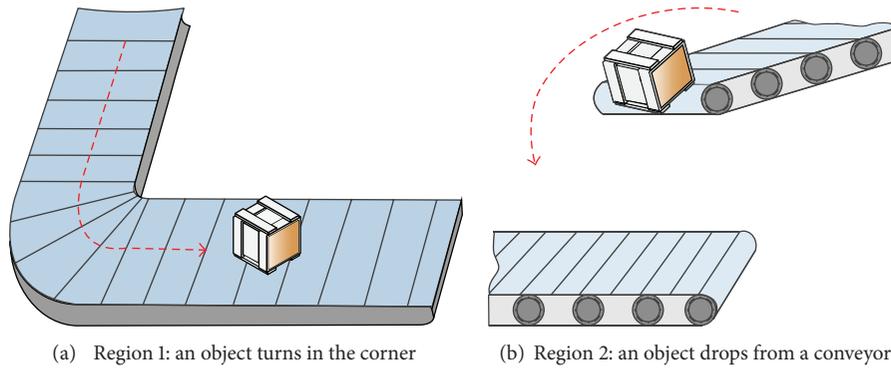


FIGURE 2: Typical essential surveillance regions where accelerometer data pattern changes sharply. Such object movements can produce distinguishable activity changes over time.

and poor scalability caused by the battery replacement. The work proposed in [19] aims to discover anomalous driving patterns from taxi's GPS traces for detecting driving frauds or controlling the traffic in modern cities. For enabling the vibration and trajectory detection, prior works often deploy high-cost sensing devices or complex deploy strategies but still suffer from coarse granularity in trajectory detection. In this paper, we aim at providing an efficient trajectory management solution with only low-cost CRFID tags, which highlights the implementation of Tracer.

3. Backgrounds and Motivating Examples

In this section, we show the background of CRFID tags and observations that reflect the feasibility of adopting accelerometer-enabled CRFID tags to identify the anomalous trajectories of objects. The “normal” situation means that the luggage is moving along the legitimate path on the conveyor. “Abnormal” situation describes that the luggage may meet any anomalies that occurred in the procedure of transportation. We present four kinds of trials to illustrate our observation.

3.1. Computational RFID Tags. In our system, we select passive WISP tags as the CRFID tagging devices. WISP tags are developed by Intel. The WISP tag is compatible with the EPC protocol [22]. A WISP tag is embedded with a 16-bit MCU (8 MHz clock rate, 8 KB flash memory, and 256 B RAM). As the first programmable passive RFID system, WISPs have been implemented to sense light, temperature, strain, and so forth. Specifically, the WISP tag has an onboard 3D accelerometer, which can sense the vibration and report the data of the three-axis to the backend server. We then leverage this function to support the moving pattern training and discrimination of trajectories. Note that Tracer only needs the accelerometer data of WISP tag. We will develop tailored and low-cost CRFID tags based on WISP in our future work.

3.2. Acceleration Pattern of Moving Objects. We report the average results of 30 similar moving traces of the tag. For visualization, only accelerometer readings are shown in

Figure 3 and measured in degrees. Figure 3(a) shows the acceleration changes collected from a stable WISP tag, and the degrees around each axis remain stable over time. We chose various WISP tags and found the noise from WISP tags with a magnitude generally no larger than 7° . Thus, if the change of degrees is not larger than 7° on any axis, the object keeps static. When the WISP tag moves along a line, the acceleration changes smoothly with a magnitude no larger than 50° between two adjacent sample points, as shown in Figure 3(b).

Figures 3(c) and 3(d) show the accelerometer data produced by two typical movements in critical areas. We find that continuous fluctuations over 80 ms indicate turns at the corners, and the sudden drops can lead to severe accelerometer data changes over 200° on horizontal axis. Therefore, it is easy to build the correlation between the movement and the collected data using a simple training process, like CART or PCA [23]. Each movement sample can be classified into a specific moving pattern, with which we can form the normal pattern of moving objects along legitimate routes.

4. Trajectory Management Framework

In this section, we first introduce the design of our CRFID based logistics system. We then present the tree-indexed Markov chain framework. By adopting our statistical framework, we can efficiently detect the anomalous trajectories instead of passive tag-based solutions. Table 1 summarizes some important notations used in this paper.

4.1. Framework Overview. Our computational RFID-based logistics system consists of WISP tags, RFID readers, and backend server. We employ off-the-shelf RFID readers which follow the EPC standard [22]. The system architecture is illustrated in Figure 4. At the essential processing areas in logistics applications, we deploy RFID readers for monitoring. We attach each object, for example, a piece of luggage or a package containing a valuable item, with a WISP tag. The backend sever can log the trace of each WISP tag from its accelerometer data.

Our framework works in three phases.

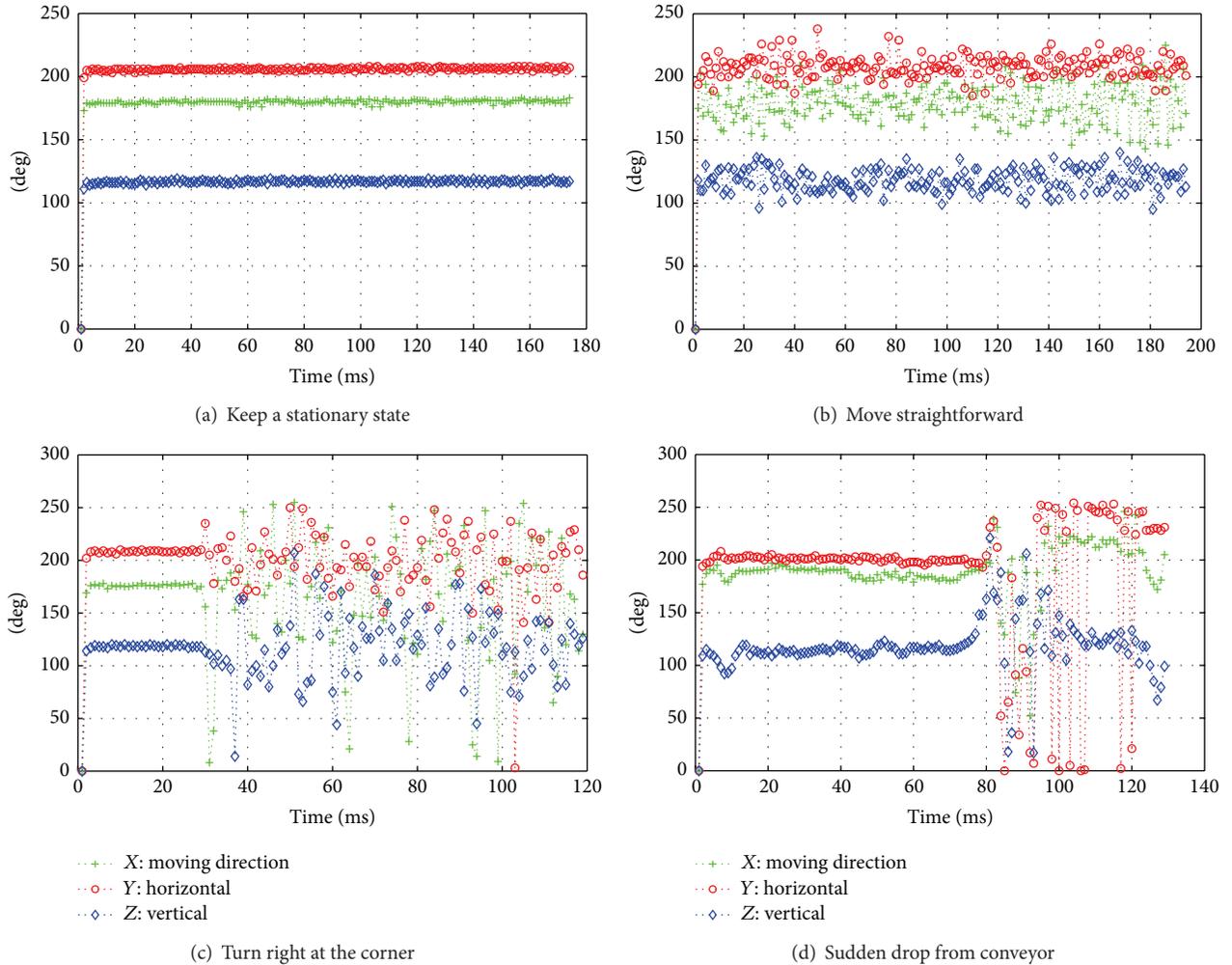


FIGURE 3: Accelerometer data obtained from various movements of an object attached with a WISP tag.

In the first phase, we formulate the whole system status into a tree-indexed Markov chain. Before the real implementation, we perform a training process on all behaviors of tags to derive the legitimate patterns of correct trajectories' transition probability matrix Q_0 .

In the second phase, we then conduct a composite hypothesis test to verify whether the sequence has been generated from the legitimate trajectories (Q_0) or other unknown trajectories generated from law Q_1 .

In the third phase, we can derive the valid patterns from those legitimate trajectories and decide whether the trace of a given tag is "normal" or "abnormal" based on those patterns.

4.2. System Model and Problem Statement. We consider a general tree-indexed Markov model that represents the moving pattern of objects on the conveyor. The tree is initialized based on the data derived from the trained trajectories. When an object enters the system, its state will correspond to a node in the tree. If an object's state is stable for a period, it will stay in the current node during this period. When its

acceleration data changes in various forms, the object will transfer from its current node to one of its child nodes in the tree. There are two types of events that may cause acceleration change, turning, and dropping. Thus, the tree is a binary tree in our system. In the tree, an object moves to its left child if it experiences a drop, otherwise to its right child after a turn. For example, in Figure 5, when an object enters the system, it first turns in one conveyor. Later, it drops to another conveyor and then turns again. Correspondingly, the object traverses the tree along the path represented by the bold line. Based on the trained trajectory, we can initialize the tree containing legitimate trajectories of objects. The problem thereby becomes as follows:

given all objects and their paths in the tree,
how to detect the anomalous events?

Consider the example in Figure 5 again. If the object stays at a node for a long period that exceeds some time-out setting, or its path extends to some unknown states in the tree, an anomalous event may occur. For example, if an object drops

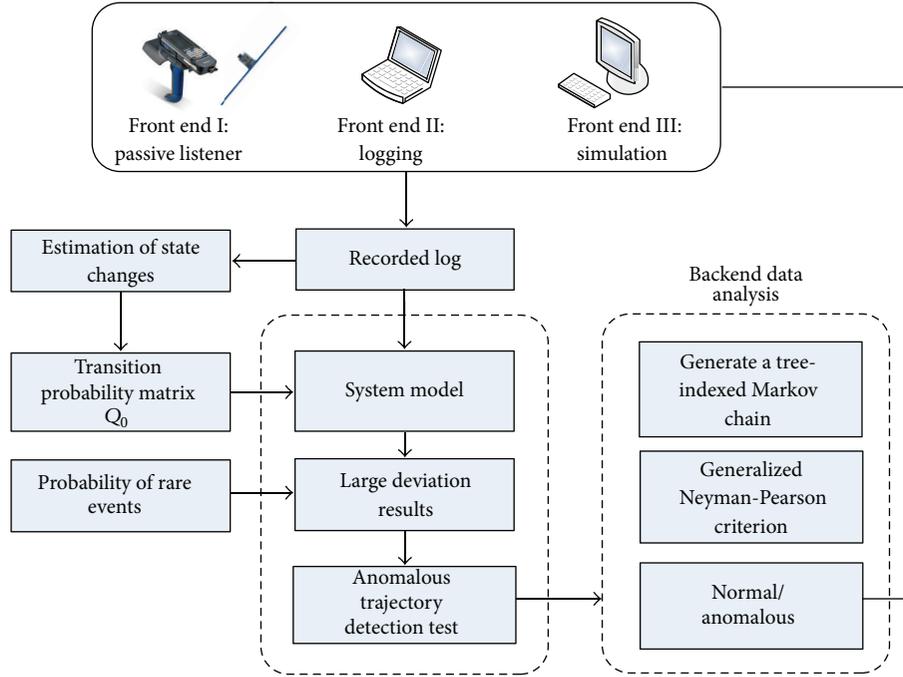


FIGURE 4: The main framework of Tracer for CRFID based logistics system.

TABLE 1: Important notations.

Symbol	Definition
$X(i)$	The state of node i in the tree T
Q_i	Transition probability matrix
L_X^n	Empirical measure of X as the m^2 -dimensional vector
P_{Q_i}	The probability evaluated from law Q_i
$I_p(\cdot)$	Large deviation rate function associated with the law $p(\cdot)$
$P_{\theta}[\cdot]$	Probabilities under the law $p_{\theta}(\cdot)$
Λ_n	Anomalous trajectory set associated with any arbitrary decision rule \mathcal{T}_n
\mathcal{T}	A decision test for detecting whether the trace is normal or not
$T = (\rho, V, E)$	A finite tree with root ρ and sets of vertices and edges denoted by V and E
$Z = (z_1, z_2, \dots, z_t)$	A recent trace of states collected from CRFID tags

out of the conveyor at the “A” point, it generates an unknown state, marked with a dash line in the tree. In this case, we need a proper tool to decide whether the corresponding trajectory is anomalous or not, where Tracer enters the picture.

Let the tree $T = (\rho, V, E)$, where ρ , V , and E denote the root, vertices, and edges, respectively. Each node in the tree represents a state selected from a finite set \mathcal{X} . We use $X(i)$ to denote the state of node i . Without loss of generality, we select $X = \{1, 2, \dots, m\}$. Then, we give a discrete probability law ν on \mathcal{X} and a $m \times m$ transition probability matrix $Q_0 = (q_0(b | a))_{a,b=1}^m$.

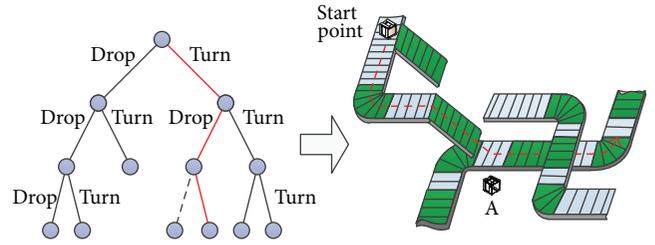


FIGURE 5: We construct a tree such that every leaf node is a sample point of the object states, and the states indicate movement changes with a typical event occurring in the logistics system. The red line depicts a legitimate trajectory of an object, and if the object drops out the conveyor, the state will turn to be unknown.

From the illustration of the tree-indexed Markov model, the problem we studied can be stated as follows.

First, we construct a new random tree starting from the root ρ . We independently select $N(v)$ nodes from V as the v 's children. The $N(v)$ is determined according to a discrete probability distribution $p(\cdot) = P[N(v) = \cdot]$ such that $0 < p(0) < 1$. We then allocate a state to each node. Let $X(\rho)$ represent the state of the random tree. For each node v , let $X(v)$ represent its states, conditioned on the state of its parent node by adopting the transition probability matrix Q_0 . Here, we employ the acceleration pattern as a source of calculating Q_0 .

In the application of trajectory management, if an anomalous event happens on one node, the trajectory tree remains stable. Furthermore, we suppose that a state i measures a vector x_i of quantities in its situation and passes the state information on x_i to all nodes. We consider a fixed time

interval $[0, t]$ and define the state of a node depending on the average value of x_i in $[0, t]$ and the corresponding values x_j of nodes that communicate with i . As a consequence, the state of the children is influenced by the state of the parent.

Then, the transition probability matrix Q_0 can be estimated from a sequence of past observations from the accelerometer data. The question now can be transformed as, given a recent trace of states $Z_t = (z_1, z_2, \dots, z_t)$ (implying a path in the tree), we seek to detect whether this sequence has been generated from the law Q_0 or from other unknown law Q_1 . We aim to differentiate between a known law Q_0 (hypothesis H_0) and an unknown law Q_1 (hypothesis H_1) using composite hypothesis testing, and a decision test could be defined as follows.

Definition 1. A decision test \mathcal{T} is a sequence of maps $\mathcal{T}^t : \sum^t \rightarrow \{0, 1\}$, with the interpretation that when $Z_t = (z_1, z_2, \dots, z_t)$ is observed, H_0 is accepted (H_1 is rejected) if $\mathcal{T}(Z_t) = 0$; otherwise H_1 is accepted (H_0 is rejected) if $\mathcal{T}(Z_t) = 1$.

The accuracy of a decision test \mathcal{T} is characterized by the type I and type II errors, which is known as false positive (FP) errors and false negative (FN) errors. The probabilities that the two types of errors occur are

$$\begin{aligned} \alpha_t &\triangleq P_{Q_0} [\mathcal{T}^t \text{ rejects } H_0], & (\text{false positive error}) \\ \beta_t &\triangleq P_{Q_1} [\mathcal{T}^t \text{ rejects } H_1], & (\text{false negative error}), \end{aligned} \quad (1)$$

where P_{Q_i} is a probability evaluated by law Q_i . Since we cannot minimize both error probabilities at the same time, we consider the optimal criterion known as generalized Neyman-Pearson criterion [24].

Definition 2 (generalized Neyman-Pearson criterion). For a given $\delta > 0$, if a test \mathcal{T} is optimal among all tests that satisfy

$$\limsup_{t \rightarrow \infty} \frac{1}{t} \log \alpha_t \leq -\delta, \quad (2)$$

the test \mathcal{T} maximizes the asymptotic exponent of the FN error probability.

4.3. Probability of Anomalous Events. We consider a determinate instance of the random tree and a realization X of the tree-indexed Markov chain, that is, a recent leaf-root path. Indeed, this path reflects the continuous state changes of the logistics system. The large deviation results can figure out the probability of anomalous events occurring under the condition mentioned in Section 4.2.

We define the empirical pair measure L_X as

$$L_X(a, b) = \frac{1}{|E|} \sum_{(v_1, v_2) \in E} \delta(X(v_1) = a, X(v_2) = b), \quad (3)$$

where (v_1, v_2) denotes an edge of the tree between the parent v_1 and child v_2 .

The authors in [25] prove a large deviation principle for L_X with a n -nodes tree. They assume the tree is critical. The

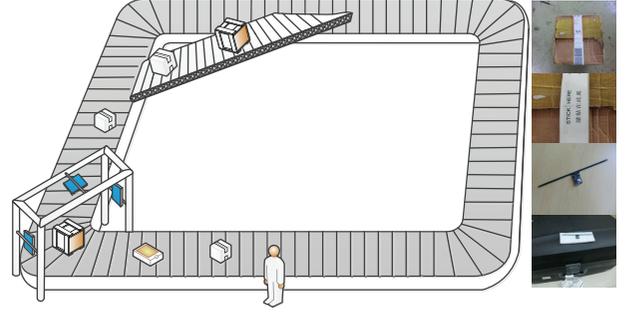


FIGURE 6: Deployment of Tracer on the baggage handling system.

assumption can be relaxed by redefining the $I_p(\cdot)$ [26]. For each probability law μ on $\mathcal{X} \times \mathcal{X}$ we let μ_1 and μ_2 denote the two marginals, so that $\mu_1(a) = \sum_{b=1}^m \mu(a, b)$ and $\mu_2(a) = \sum_{b=1}^m \mu(b, a)$.

Let $I_p(\cdot)$ denote the convex dual of the generating function of the offspring law $I_p(\cdot)$:

$$I_p(x) = \sup_{\lambda \in \mathbb{R}} \left\{ \lambda x - \log \left(\sum_{n=0}^{\infty} p(n) e^{\lambda n} \right) \right\}. \quad (4)$$

It is known as Cramer's theorem [27] that $I_p(\cdot)$ is the large deviation rate function correlated with the law $I_p(\cdot)$. Therefore, we define $\mu_1 \otimes Q_0$ as the vector with elements $\mu_1(a)q_0(b | a)$, $a, b = 1, 2, \dots, m$, and let \ll indicate strict inequality between vectors.

Theorem 3. Assume that T is a tree with offspring law $p(\cdot)$ such that $0 < p(0) < 1 - p(1)$, $\sum_l p(l) = 1$, and $l^{-1} \log p(l) \rightarrow -\infty$. Let X be a Markov chain indexed by T , which initially follows arbitrary distribution and an irreducible transition probability matrix Q_0 . Then, for $n \rightarrow \infty$, the empirical pair measure L_X conditioned on $\{|T| = n\}$ satisfies a large deviation principle in the space of probability vectors on $\mathcal{X} \times \mathcal{X}$ with speed n . The good rate function is

$$I(\mu) = \begin{cases} H(\mu \| \mu_1 \otimes Q_0) + \sum_{a=1}^m \mu_2(a) I_p\left(\frac{\mu_1(a)}{\mu_2(a)}\right) & \text{if } \mu_1 \ll \mu_2 \\ \infty & \text{otherwise,} \end{cases} \quad (5)$$

where $H(\cdot \| \cdot)$ denotes the relative entropy between two probability vectors defined in [28] and μ_1 and μ_2 are the first and second marginal of μ and $\mu_1 \otimes Q_0$.

Note that the first term in (5) characterizes large deviations of the assignment of states to the nodes, while the second term is related to the structure of the tree. In fact, we could also adopt the result to deal with noncritical trees, since non-critical trees are also important for detecting anomalous object states.

4.4. Anomalous Trajectory Detection Test. In this section, we propose an anomalous trajectory detection test that can

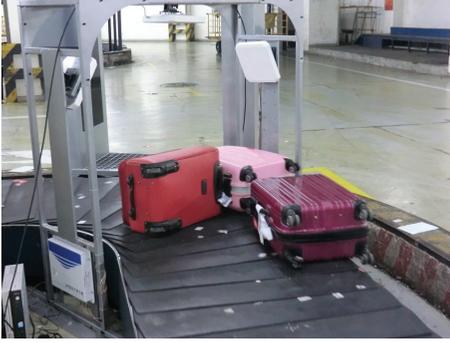


FIGURE 7: RFID readers are deployed into the essential processing regions.

detect the anomalous trajectories with minimized false negative error. Therefore, we need to demonstrate the detection test is optimal in a generalized Neyman-Pearson criterion.

Given a sequence of realizations X^k of the tree-indexed Markov chain, the tree T is with n nodes. We can approximate the offspring law $p(\cdot)$ and the transition probability matrix Q_0 by taking the corresponding samples. Specifically, if L_{X^k} is an empirical measure of the k th realization (3), then $(\sum_{l=1}^k L_{X^l}(a, b)/k)/(\sum_{l=1}^k \sum_{b=1}^m L_{X^l}(a, b)/k)$ converges to $q_0(b | a)$ with the probability approaching one as $k \rightarrow \infty$. Alternatively, we can compute the frequencies on a single large tree when $n \rightarrow \infty$.

Suppose that we have estimated $p(\cdot)$ and Q_0 from the previous trajectories. $p(\cdot)$ and Q_0 determine whether a specific realization X is anomalous. As discussed in Section 4.2, we need to differentiate $p(\cdot)$ and Q_0 (hypothesis H_0) from other unknown law Q_1 (hypothesis H_1).

Then, we denote the empirical measure of X derived from (3) by L_X^n , where the superscript n indicates that the tree has n nodes. The following theorem provides an optimal test for the tree-indexed Markov chain, which is the test of anomalous trajectory detection.

Theorem 4. *The decision test $\mathcal{F}_2^{*,n}(X)$*

$$\mathcal{F}_2^{*,n}(X) = \begin{cases} 0, & \text{if } I(L_X^n) < \delta, \\ 1, & \text{otherwise} \end{cases} \quad (6)$$

is optimal according to the generalized Neyman-Pearson criterion.

As we concentrate on the anomaly detection approaches, proof of the theorem has been omitted, and a similar proof can be found in [26].

Based on these theories, the anomalous decision test can be executed in our system in order to judge whether the moving objects obey the legitimate patterns of correct trajectories' transition probability matrix Q_0 . If the decision test accepts the hypothesis H_0 , that addresses the trace is collected from a correct path of tree T ; otherwise, otherwise, the decision test will accept H_1 and conclude that the trace is collected from anomalous trajectories. Furthermore, we can derive the valid patterns from those legitimate trajectories

and decide whether the trace of a given tag is "normal" or "abnormal" based on those patterns.

5. Evaluation

We conduct trace-driven simulations and evaluate Tracer over training data sets and several real test samples. We perform the preliminary deployment of Tracer on the baggage handling system (BHS) at Terminal 2 of Beijing Airport, as shown in Figure 6.

5.1. Experimental Setup. During the implementation, we face a challenging issue of the interrogation range. The interrogation range depends on the communication range of backward channel. The reader usually adopts pulse-interval encoding (PIE) mechanism to code commands or data. This selection enables easy demodulation for the extremely resource-limited tags. On the contrary, the tag employs Miller 4 as the encoding mechanism for high throughput as well as low bit error rate. Meanwhile, much more energy consumed by MCU and sensors on WISP tags further shortens the interrogation range significantly compared to common passive tags [29].

In addition, existing commercial readers do not provide programming interfaces to achieve fine-grained interrogation parameters tuning. As a result, the communication between commercial readers and WISP tags is not well optimized. Therefore, we develop the reader specifically tailored for our system but still compatible with the EPC C1G2 Air protocol [22] and following the FCC regulation. It works on the frequency of 860–960 MHz and transmits at a power of 30 dBm over 8 dBi gain circularly polarized antennas. The interrogation range of tags can be expended to 1.5–3 m.

In our preliminary implementation, we test Tracer over 6 flights. We randomly attach WISP tags to some volunteer passengers' luggage. The information of the passenger, for example, the flight number, is encoded and stored into the EPC field in the bag. Those bags then enter into the sorting area of BHS. The size of sorting area is around 50 m × 20 m, with a rectangle belt conveyor and an incline belt conveyor. We deploy the RFID reader into two types of the processing regions, the junction between two conveyors and the corners of conveyors, as shown in Figure 7. The bags are sorted based on flight numbers. Tracer jointly works with the BHS. As we present in Section 3, the data collected by Tracer includes 6 dimensions, including the time of detection, sensor type, EPC code, and three-axis accelerometer data. Tracer injects the collected accelerometer data into its tree-based Markov chain framework and reports the anomalous trajectories of luggage during the process in real time. From the traces collected from WISP tags, we generate 3000 data sets for simulating large-scale logistics systems. Later, we also employ the real trace to examine the soundness of our simulation results.

5.2. Metric and Methodology. In our experiments, we employ the following metrics to evaluate the performance of Tracer.

Response time: we define the response time as the time that Tracer will consume after the anomalous events happen.

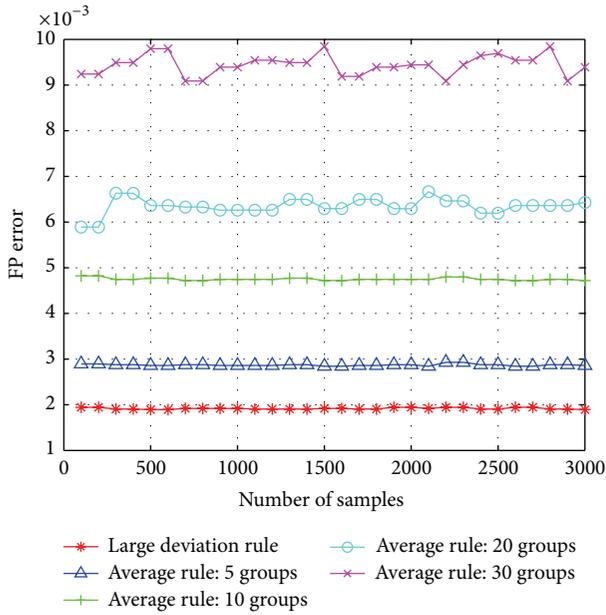


FIGURE 8: FP error (linear scale).

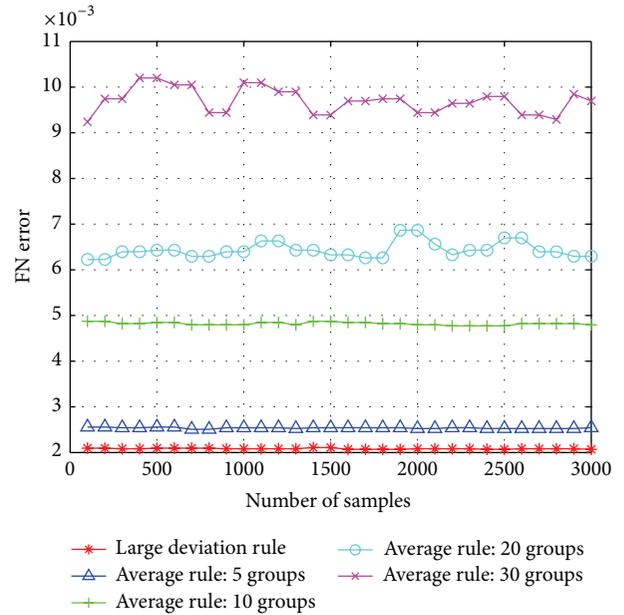


FIGURE 10: FN error (linear scale).

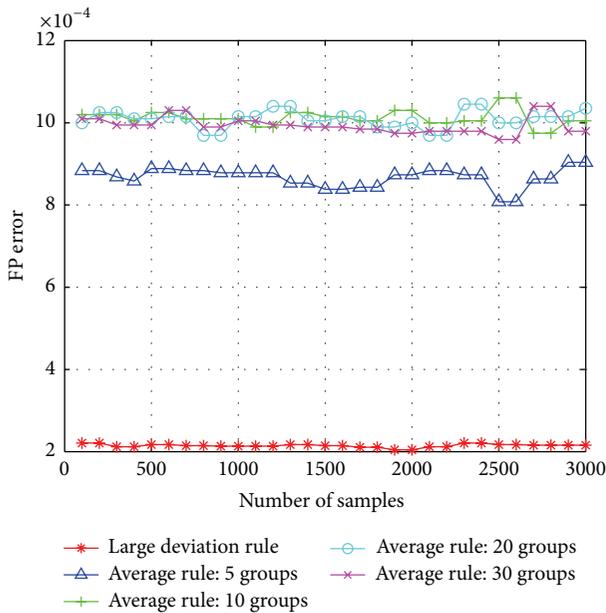


FIGURE 9: FP error (log scale).

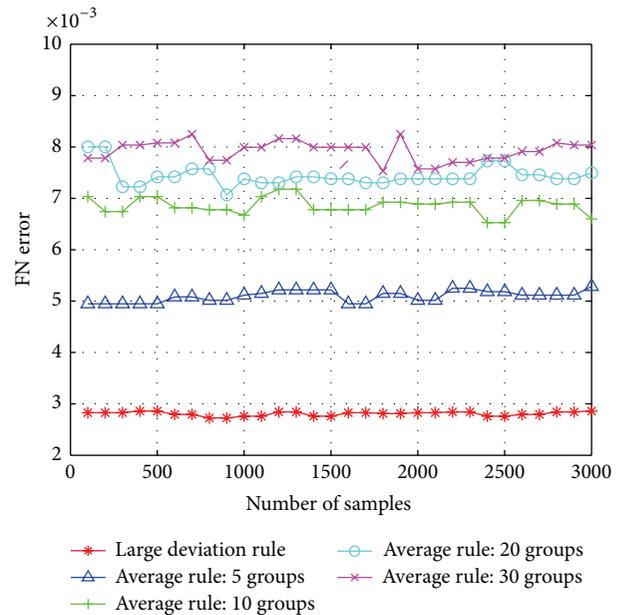


FIGURE 11: FN error (log scale).

This is a critical parameter to reflect the efficiency of Tracer in real logistics applications.

Error probability: we evaluate the accuracy of Tracer using the number of errors. There are two major types of errors that may occur in Tracer, false positive (FP) error and false negative (FN) error, as we have discussed in Section 4.2. An FP error means that Tracer reports an anomalous trajectory which indeed does not happen, while an FN error means that Tracer fails to report an anomalous trajectory which has really happened.

Following the model of Tracer proposed in Section 4.2, a tree is generated with an estimated probability distribution. The nodes in the tree monitor anomalous events and for each observed event, they send information back to the root. In our simulations, the events at each node occur according to independent Poisson processes. Our goal is to detect changes in the event generation rates as described in Section 4.4. The offspring law $p(\cdot)$ is uniform in $\{0, 1, \dots, 10\}$. It can be easily found that the state of each node depends on the average times of event happening per unit time through the node. The average times of event happening are mapped to 10 states. The

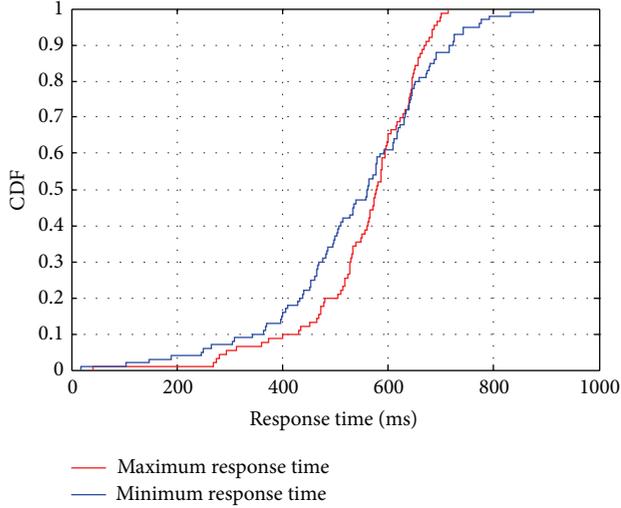


FIGURE 12: Minimum and maximum response time.

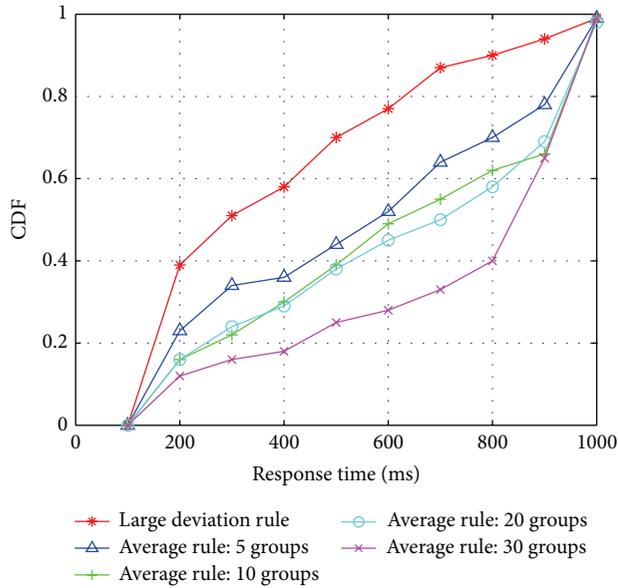


FIGURE 13: CDF of response time.

transition probability matrix Q_0 is estimated from anomaly free traces.

Considering a determinate tree, the empirical measure L_X is calculated in a distributed way; each node keeps a vector of counts of downstream nodes in a certain state. When a node changes its state, the corresponding value in this vector is changed and this update is propagated up the tree. Note that distributed computation is useful in implementing anomalous trajectory detection techniques. We employ the detection test of Theorem 3, where the anomaly free law $p(\cdot)$ and Q_0 can be calculated from observations before the anomaly is introduced. We deliberately generate an anomalous trace which interferes with a state change on the tree. As a result, the node changes its parent and the anomalous trajectory can be detected.

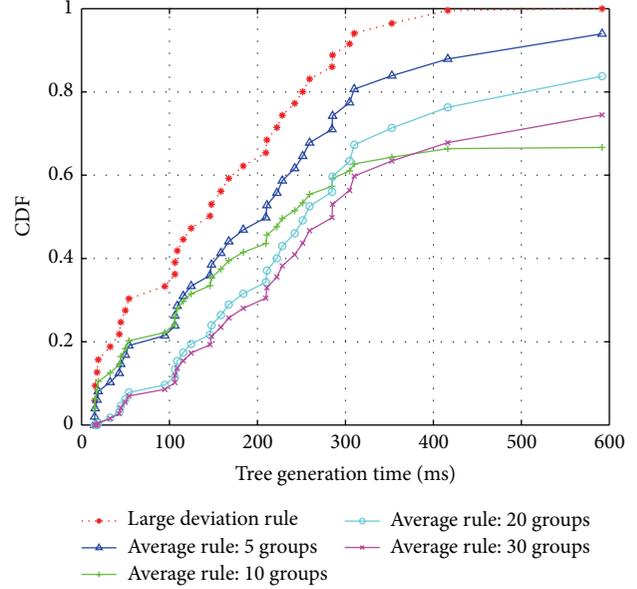


FIGURE 14: CDF of tree generation time.

5.3. Accuracy of Tracer. To aid the detection, we utilize trained data of “normal” trajectories as the ground truth. Consequently, Tracer can make correct decision during the trajectory detection. Tracer adopts the large deviation rule as described in Section 4.3. To testify the effectiveness of our method, we compare the large deviation rule adopted by Tracer with other average rules. The average rules are coming from grouped samples. We divide the trace into several groups (5, 10, 20, and 30) based on their depth of the tree. Average measurements are collected from the samples in the same group and compared to a threshold, which is derived from the estimation on our traces. If any groups that deviate from the threshold, then an anomalous event is detected.

The comparison results between Tracer (large deviation rule) and other average rules are reported in Figures 8–11. Figures 8 and 9 show that the FP error of large deviation rule is 1.5x smaller and 4x smaller than all average rules under linear scale and log scale, respectively. Figures 10 and 11 show the FN error in linear scale and log scale under different rules, and Tracer outperforms average rules (5 groups) almost 1x and 2x, respectively. Figures 15 and 16 plot the CDF of FP error probability and CDF of FN error probability. Both of the two figures demonstrate that the FP and FN error probability of Tracer are relatively smaller than other average rules. Figure 18 describes the detection accuracy of Tracer by adopting large deviation result; it outperforms other situations as expected. The ROC curves shown in Figure 19 are drawn for Tracer and other average rule approaches. The result demonstrates that the large deviation rule outperforms all average rules; that is, the large deviation rule has the smallest FN error probability for any fixed FP error probability.

It is clear that the amount of FP errors induced by Tracer is static. This demonstrates that Tracer performs well in terms of accuracy as well as scalability.

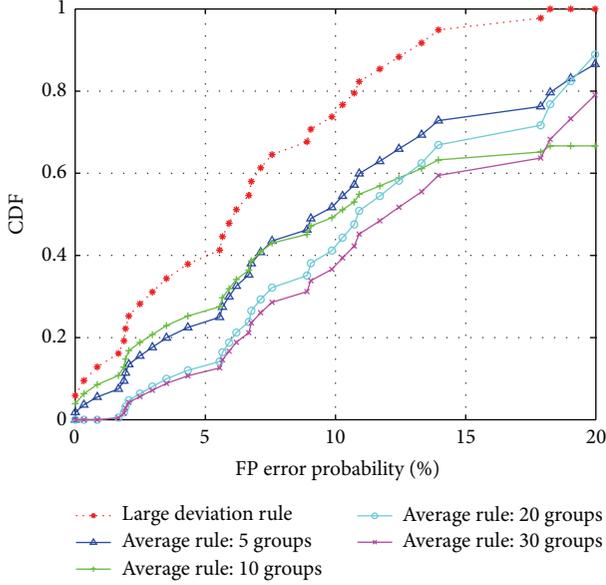


FIGURE 15: CDF of FP error probability.

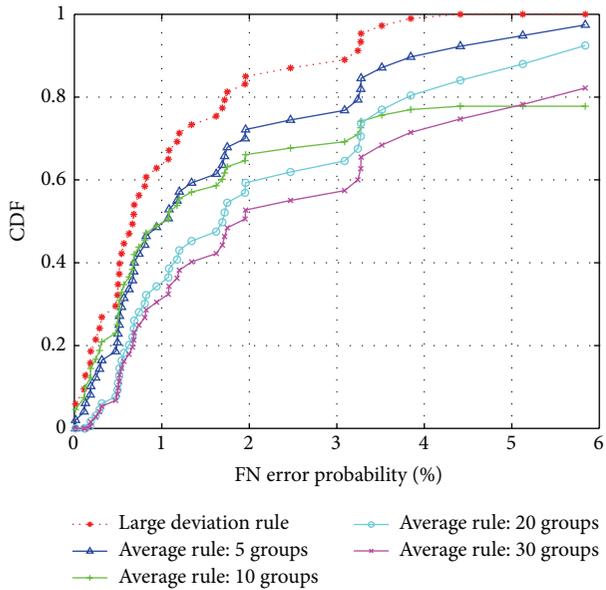


FIGURE 16: CDF of FN error probability.

5.4. *Efficiency of Tracer.* From Figure 17, the average response time is calculated from 30 trials. Tracer remains a little longer than the theoretical results when the average response time is under 800 ms. Tracer performs better when the average response time is above 800 ms. With a relatively high average response time, the result of Tracer converges faster than the theoretical result.

Figure 12 shows the comparison between the minimum response time and maximum response time with 30 trials. The result demonstrates that the gap between the minimum response time and maximum response time is small, which

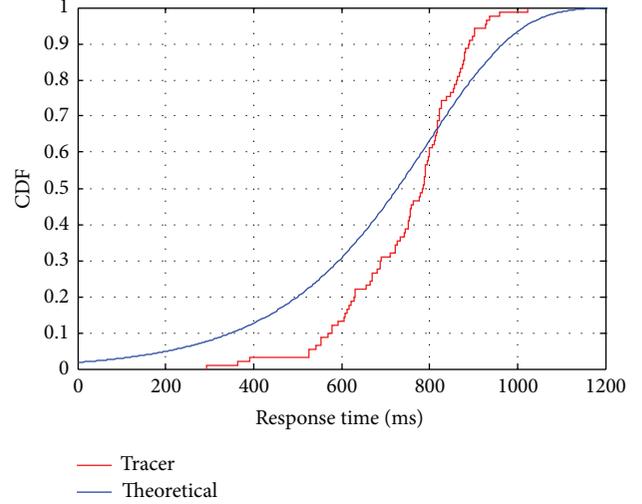


FIGURE 17: Average response time CDF of Tracer and theoretical results.

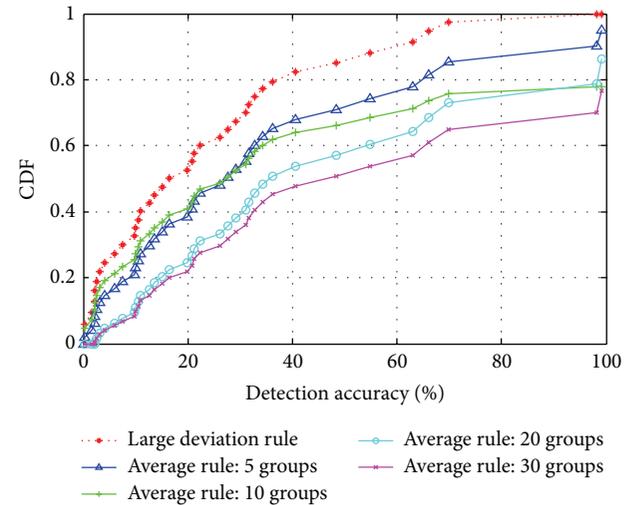


FIGURE 18: CDF of detection accuracy.

provides us an efficiency guarantee on using Tracer to detect anomalous trajectory in logistics systems.

Figure 13 shows the response time comparison under different rules. We find that, in 70% of cases, the response time of Tracer is under 500 ms, indicating that Tracer outperforms other average rule methods; the detection response time is always at an acceptable state. Figure 14 describes the time used for the tree generation of the tree-indexed Markov model, and the tree generation time of other approaches is no better than Tracer.

6. Conclusion

In this paper, we propose a tree-indexed Markov chain to characterize the movements of objects in logistics applications. By adopting the statistical test and CRFID tags, our

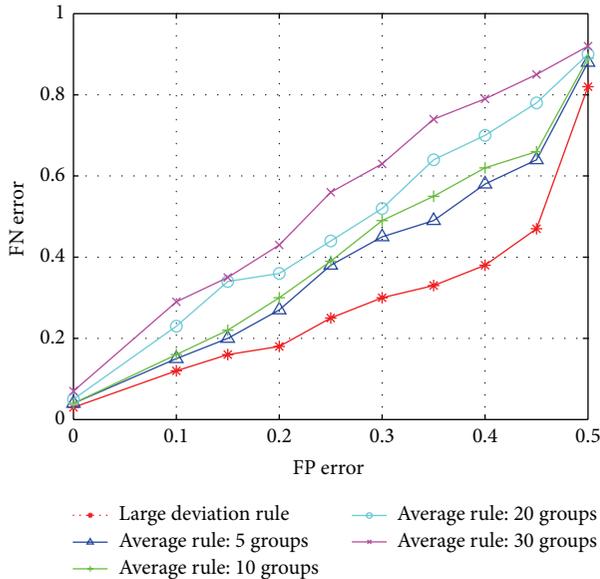


FIGURE 19: Comparison of ROC curves.

approach, Tracer, can effectively detect anomalous trajectories. Specifically, our framework is general to be applied for statistically detecting significant temporal or spatial changes. We believe this is a step towards fine-grained anomalous trajectory detection in logistics applications, even though some future works, for example, developing cost-efficient CRFID tags, are necessary before a large-scale deployment. We also expect that the experience achieved in this work can give useful design guidance of trajectory management to future logistics applications.

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