Anomaly detection in RFID system

Khaled Garri, Francoise Sailhan, Samia Bouzefrane, Marc Uy

Cedric Laboratory, Conservatoire National des Arts et Métiers, 292 rue Saint Martin, 75141, Paris, France

name.surname@cnam.fr

Abstract: The level of sophistication exhibited by RFID tags is not only affecting their financial cost but also their ability to provide (extensive) cryptographic functionalities. It follows that low-cost tags offer no real control access. To tackle this issue, we propose an anomaly detection system which attempts to identify deviations from the normal behavior. In practice, subjects are equipped with RFID tags in order to be constantly located. Then, a user's profile is built, relying on the Kohonen's maps that constitute an efficient way for automatically categorizing and further compare the tag behavior against the normal user’s behavior (as expressed in the user’s profile).

Keywords: Anomaly detection system, RFID.

Biographical notes: K. Garri did his MTech in mobile and embedded system from Conservatoire National des Arts et Métiers (CNAM), Paris, France and is currently doing his PhD in Computer Science in CNAM. His areas of interest are intrusion detection, RFID and java cards.

Francoise Sailhan is associate professor in CNAM. Prior she was professor assistant in the University of Franche Comté, France, and worked as researcher in the Ericsson Ireland Research Center (EIRC), Ireland. In 2005, she successfully defended a PhD thesis at the University Pierre and Marie Curie, France, her Phd work taking place in INRIA, France**.** Her research interests are wireless networks & intrusion detection.

Samia Bouzefrane is an associate professor at the CNAM of Paris. She received her Ph. D. in Computer Science in 1998 at the University of Poitiers (France). She joined the CEDRIC Laboratory of CNAM on September 2002 after 4 years at the University of Le Havre. After many research works on real-time systems, she is interested in smart card area. She took part in the MESURE project to evaluate the performance of Java Card platforms, that has been awarded. Currently, she works on the security and the service oriented-architecture of smart objects. Furthermore, she is the author of two books: a French/English/Berber dictionary (1996) and a book on operating systems (2003). Since 2008, she is a member of the ACM-SIGOPS board, France Chapter.

Marc Uy did his Master in mobile network and embedded system at CNAM, Paris, France. His research areas include sensor network monitoring and intrusion detection.

1. Introduction

Radio Frequency IDentification (RFID) is a technology which is primarily intended to identify automatically any object. As such, RFID is nowadays considered as one of the mostly used wireless technology in security-related domains including, electronic payment, access control and transport. A RFID system consists of tree main components, a RFID tag (basically, a silicon microchip attached to an antennae) and possibly enriched detection system identifies a spoofing attack wherein an adversary mimics an authentic tag and any usage of a robed tag, because these intrusions, by assumption, deviate from normal usage of the users. We further prototyped our anomaly detection and conducted preliminary experiments.

This paper is organized as follows. We first define the use-case targeted by our anomaly detection system and evaluate existing systems against the requirements driven by our use case (Section 2). Then, we present the proposed anomaly detection system (Section 3) and further evaluate its performance (Section 4). We finally conclude with a summary of our contribution along with directions of future work (section 5).

2. Control Access based on RFID

We consider a scenario that consists in controlling the access to a building corresponding to a computer science laboratory and in detecting intruders. Each researcher of the laboratory owns a cell phone rather than a badge, used to access the laboratory building. The cell phone is endowed with a RFID tag. This constitutes the first level of security. In order to detect an intruder who enters in the building despite of the access check, we add to our RFID system, a traceability system built thanks to the geo-localization of the tags carried by the staff. This constitutes the second level of security.

In this scenario, only one category of tag attacks is considered: the stolen, cloned and spoofed tags. If an intruder accesses a laboratory building, her/his behaviour differs from a legitimate user that owns some habits when she/he is working within the laboratory. The idea is to build a reference model based on the habits of the laboratory researchers during a time period. Then, the behavior of any user entering the building is compared to the reference model. A significant deviation is defined as an intrusion. Within such a scenario, the trajectory of any subject is sampled at discrete time intervals $t_{1,}$ …, t_k, …, t_m with *m* defining the trajectory length. Any observation is expressed as a set of *m* *n*-dimensional real *vectors* $x(t_k) = (x(t_1),\ ..., x(t_k), ..., x(t_m))$. Note that we assume more samples than rows in the observation (i.e., *m* >> *n*). A trajectory is hence composed of spatio-temporal records, each record being primarily composed of:

- A geographical location within a 3D plan,
- A temporal attributed, i.e., a timestamp. Note that records are collected at arbitrary time intervals.

In addition to the above, extra pieces of information may be added or inferred from the spatio-temporal records defined above. They relate to the e.g., duration separating two samples, maximum speed, (estimated) attractor point, direction, movement pattern (e.g., loop, u-turn) and the average, or standard deviation of the aforementioned parameters.

Anomaly detection in RFID system

2.1 Related Work

Research tackling anomaly detection in RFID systems still remains in its infancy. Two anomaly detection systems [MH07, TS08] have been initially proposed. In order to find an abnormal behavior (e.g., a change in the tag ownership), both rely on a statistical method (i.e., standard deviation and mean) inspirited by the pioneering[1] work of Denning [DE87]. Precisely, the former measures the number of times a user logs into a system (i.e., the number of tag reads) at different locations, whereas the latter also encompasses the number of tag writes, the time interval between two readings (*versus* 2 writings) and the received signal strength. Based on the aforementioned indicators, the former identifies changes in the ownership (as it is the case with e.g., cloned or robed tags) whereas the latter introduces the notion of watchdog reader, i.e., a reader dedicated to monitoring tags and readers in its reading range so as to detect a MIM (Man In the Middle), i.e., a malicious reader that either writes false data on writeable tag or intercepts reading request and relays it to a malicious tag emulator so as to provide to a malicious user an access to the tag reader. The observations cached by any reader and watchdog reader are forwarded to the anomaly detection system and any deviation is defined as an anomaly. Still based on statistical data, the intrusion detection system proposed in [YGD10] makes use of the rate of command matching, password succeeding and Cyclic Redundancy Check (CRC) fails in order to detect intrusions relating to password guessing, DOS (Denial Of Service) based on e.g., RF signal interfering and MIM. The basic idea is that attacks are made of test operations that usually fail. Thus, a *ratio* e.g., number of succeeding passwords over the total number of attempts, is used to define a danger signal, which is further collaboratively detected relying on artificial immune system. In [EV10], the notion of location is refined by distinguishing physical and semantic location (i.e., a geographical location/area wherein a RFID reader operated and the meaning of that location/region, e.g., a room number). The interpretation of the (physical and semantic) location information is further facilitated by relying on an ontology-based intrusion detector which makes use of an inference system in order to automatically reason on anomalies. In practice, an anomaly refers to a RFID tag that is either read to many times within a fixed duration with respect to the usage condition or not moving according to the static path in the supply chain (as predefined in the object profile). Note that, similarly, this last indicator is used in [LMF07] in order to pinpoint illicit players that inject counterfeits tagged objects in a licit supply chain. Nevertheless, in this latter case, the intrusion detection is obtained relying on hidden Markov chains rather than rules.

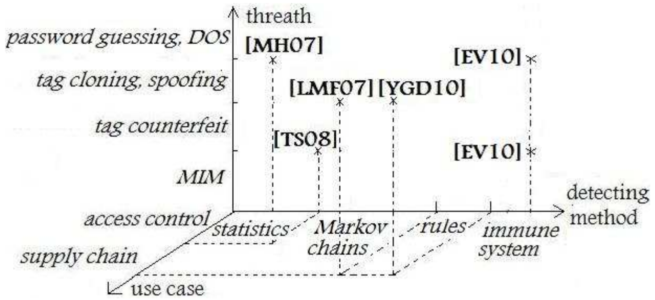


Figure 1: Taxonomy

[1] For a survey on anomaly detection, interested reader may refer to [CBK09].

Reference	*threat*	*use case*	*detection method*	*profile*	*anomaly indicators*
MH07	tag cloning & spoofing	simulated attack given a real-world test-bed: the access control in a computer science department	Statistics	tag profile: profile name, read/write operation, value of current observation, past observations	number of times a tag has been used
TS08	man in the middle	simulated RFID network based on RFIDSim [MIL06]	Statistics	The tag profile is coupled with the reader profile and is divided into a read operation profile (tag id, read operation, location, timestamp) and a write operation profile (tag id, read operation, timestamp)	read/write frequencies, time interval between consecutive operations, RSS-based location
YGD10	password guess, RFID skimming, DOS	Simulated supply chain	artificial immune system	following the EPC C1G2 standard [EPC07] of EPC Global, the profile is given by (timestamp, location, reader command, EPC code, operation return flag code)	rate of: operation matches, password matches, tag responses, CRC errors
EV10	tag counterfeit	simulated supply chain	ontology-based inference system	timestamps & locations in the supply chain	time interval between 2 read operations and difference with the normal static path in the supply chain
LMF07	tag counterfeit	simulated supply chain	hidden Markov chains	timestamps & locations in the supply chain	difference with the normal static path in the supply chain

Table 1. Classification of anomaly detection

Overall, two main usages of RFID system have been considered in the aforementioned literature (see Figure 1 and Table 1 for a summary): the control access in a building [MH07] (actually the computer science department of the Tasmania University) and the supply chains [TS08,YGD10,EV10,LMP07]. The performance of the proposed anomaly detectors has been evaluated based on some simulated attacks operating either over a real test bed (for the former) or a simulated RFID system (for the latter). Mostly focused on the tag-reader relationship, envisioned threats include (i) the tag cloning/spoofing attack which may lead to e.g., the insertion of a counterfeit objects in a supply chain or an access granted to the computer department, and, (ii) the MIM or DOS attack launched by a rogue reader. Indicators of such threats fall into two categories:

- *Operational:* indicators refer to some repeated commands/operations (e.g., read/write, password check) that are either failing or differing from their normal usage (i.e., deferring from the user's habits),
- *Spatial:* indicators correspond to (i) the path followed by a tag which may differ from the well-established one or the reader position which is identified based on the signal strength and indicates the potential presence of a rogue reader.

Once recorded into an object/user's profile, one or a combination of the above indicators is used to detect intrusion, relying for this purpose on different methods ranging from statistics, hidden Markov chains, rules, up to artificial immune system.

In this context, we propose a self-classifying anomaly detection system. As in [MH07], we focus on a control access scenario wherein users (staff) working within a building, are equipped with active RFID tags, which are used to constantly monitor the user's location based on the signal strength. Thus, fine-grained and continuous user localization can be provided. Given this specific use case, anomalies are primarily[1] detected based on spatio-temporal indicators rather than operational indicators. Instead of relying on a simple statistical method, we select an advanced neural network architecture permitting to build automatically, i.e., without user's/expert's supervision, the user's profile. Note that such automatic training permits to add easily additional indicators (i.e., operational indicators), i.e., without modifying the core implementation. Consequently, based on an advanced Kohonen's map, our detection system detects any spoofing/cloning attack wherein an adversary mimics an authentic tag and any usage of a robed tag, because these intrusions, by assumption, will deviate from normal usage of the customer.

3. Anomaly Detection

When attempting to detect anomaly, the main difficulty lies in defining what a normal *versus* abnormal behaviour is. An advantage of self-organising map is that it learns to discriminate normal behavior from abnormal behavior based on examples (i.e., training samples). Thus, no explicit definition of normal/abnormal behavior is required to the user. Our anomaly detection system is based on the Kohonen map [TK82]. In a nutshell, a Kohonen map is a neural network that distinguishes itself by its unsupervised learning. Another convenient aspect is related to the fact that this map reduces the dimensionality of the input data from a (potentially) high dimension into 2- or 3-dimensional space (herein 2-dimensional), hence allowing an easy and instinctive interpretation of the results. In practice, a Kohonen-map-based detection of anomaly involves the following three phases:

- The pre-processing phase (Section 3.1) consists in filtering the raw data provided by the RFID system,
- The training phase (Section 3.2) aims at learning the habits of the subjects in order to build Kohonen maps, and,
- The anomaly detection phase (Section 3.3) makes use of Kohonen maps in order to detect anomalies.

Parameter	***Description***
M	Trajectory length
$x(t_1),\ \ldots, x(t_k), \ldots, x(t_m)$	User's trajectory defined as a set of *m* observations taking place at time $t_1, \ldots, t_k, \ldots, t_m$
$x'(t_k)$	Observation $x(t_k)$ taken at t_k, filtered and normalized
Trajectory	
S	Size of the Kohonen map
$w_1, \ldots, w_i, \ldots, w_s$	Kohonen map
$w_i\ (t_k)$	Neuron *i* of the Kohonen map at t_k

$g(x'(t_k))$	Winning neuron attributed to *x'(t_k)*
$\eta(t_k)$	Factor that adapts the degree of change imposed to a neuron at t_k
$\pi_{i,\, g(x'(tk))}(t_k)$	Neighbourhood of the winning neuron $g(x'(t_k)$ *at* t_k
Training phase	
$o(t),\ldots,o(t+q),\ldots,o(t+r)$	User's trajectory wherein anomaly is researched
$o'(t),\ldots,o'(t+q),\ldots,o'(t+r)$	Normalised user's trajectory
$D_{g(x'(t_k))}(\alpha)$	Neighbourhood of a winning neuron $g(x'(t_k))$
α	Radius circumventing the neighbouring area.
$\beta(r)$	Ratio of anomalous positions constituting a trajectory and that can be accepted.
Anomaly detection	

Table 1. Parameters

3.1 Raw Data Preprocessing

Anomaly detection is intended to identify activities that vary from an established pattern. This necessitates to (i) create a knowledge database constituted of the (previously) monitored activities and to (ii) subsequently categorize the variety of stored data relying for this purpose on the Kohonen maps. Prior being provided as input to the Kohonen maps, data is pre-processed, following a two steps process:

- *Data filtering* - Data provided by the RFID system are filtered so as to extract information that is relevant to anomaly detection.
- *Data normalizing* - Normalising input sample consists in scaling the initial data set so as to fall in the specific [0,1] range. In practice, a set of input samples that are collected at $t_1,\ \ldots, t_k, \ldots, t_m$ is expressed as a set of vectors $x(t_1),\ \ldots, x(t_k), \ldots, x(t_m) \in R^m$ with the vector $x(t_k)$ describing an activity observed at t_k. Such activity is defined as an *n*-dimensional vector of $x^T(t_k) = (x_1(t_k),\ \ldots, x_i(t_k), \ldots, x_n(t_k))$, which, once normalised, verifies: $x'^T(t_k) = (x'_1(t_k),\ \ldots, x'_i(t_k), \ldots, x'_n(t_k))$ with $x'_i(t_k) = \dfrac{x_i(t_k)}{\max_{j\in[1,n]}(x_{ij}(t_k))}$

Relying on these filtering and normalisation processes, workless samples are removed and each filtered sample is of equal footing and can hence be exploited during the training phase in order to create a Kohonen map.

3.2 Training

The training phase results in a Kohonen map $w_1,...,w_s$ of size *s* that corresponds to a topological 2-dimensional array of neurons. This map $w_1(t_0),...,w_s(t_0)$ is originally initialised (i.e., at t_0) with random values. This map is intended to categorise the normalised samples $x'(t_1)$, $..., x'(t_k),..., x'(t_m)$ provided as input. In practice, each input vector $x'(t_k)$ with *k є [1, m]*, is compared with each neuron forming the Kohonen map and a distance between the input vector and this neuron is computed. Finally, the closest neuron is selected as a winning neuron. Then, the topological structure of the Kohonen map is updated: neurons that are topologically close to the winner move towards it direction. Consequently, the resulting Kohonen map reflects a categorisation (clustering) of the samples. More particularly, assuming a measure whose norm is noted ||, the distance between an input vector *x(t$_k$)* and the synaptic vector of each neuron $w_i(t_k)$ of the map is computed and the winner *g(x'(t$_k$))* is selected according to the following law:

$$g(x'(t_k)) = \min_{i\in[1,s]} \|x'(t_k), w_i(t_k)\| \qquad (2)$$

Next, the neurons that are topologically close to the identified neuron move towards the direction of the winner. For this purpose, the neurone w_i is updated as follows:

$$w_i(t_{k+1}) = w_i(t_k) + \pi_{i,g(x'(t_k))}(t_k) \cdot \eta(t_k)[x'(t_k) - w_i(t_k)] \qquad (3)$$

with $(i, j, k) \in [1, s]^2 \times [1, m]$, $\eta(t_k)$ defining an adaptation factor that controls the degree of change imposed to the neuron vector and $\pi_{i,g(x'(t_k))}(t_k)$ a neighbouring function centred around the winner $g(x'(t_k))$. Note that both $\eta(t_k)$ and $\pi_{i,g(x'(t_k))}(t_k)$ depend of the time t_k. The basic idea is that the adaptation factor $\eta(t_k)$ decreases monotonically as the learning phase progresses so as to guarantee a convergence of the weighted neuron's vector towards a stable state [LB91]. For that purpose, $\eta(t_k) = \eta_0 \exp(t_k / t_m)$. Similarly, the neighbouring function $\pi_{i,g(x'(t_k))}(t_k)$ decreases as *t* evolves until the winning neuron is the only neuron that has its weight significantly updated. For this purpose, $\pi_{i,g(x'(t_k))}(t_k)$ is defined as a symmetric function following a Gaussian form[1] with a standard deviation $\sigma(t_k)$ decaying exponentially with time:

$$\pi_{i,g(x'(t_k))}(t_k) = \exp\left(\frac{\|(x'(t_k), w_i)\|^2}{2\sigma^2(t_k)}\right), \qquad (4)$$

[1] A Gaussian form facilitates the ordering of the neighboring set, yielding to faster convergence [LB91].

$$\sigma(t_k) = \sigma_0 . \exp\left(\frac{-t_k \log(\sigma_0)}{t_m}\right)$$

Overall, the Kohonen map is updated based on this neighbouring notion which permits to classify the observations, i.e., to group neurons into some clusters that are characterised by their high training density. Overall, the training phase can be expressed as follows:

Algorithm 1. Training phase

Given the following parameters:

- $x'(t_1),\ \ldots, x'(t_k),\ldots, x'(t_m)$ *: set of pre-processed n-dimensional input samples collected at* $t_1,\ \ldots, t_k, \ldots, t_m$ *, each of these samples x'^{T}(t$_k$) characterised by* $x'^T(t_k) = (x'_1(t_k),\ldots, x'_i(t_k),\ldots, x'_n(t_k))$,
- *|| norm related to the selected measure,*
- *s :the size of a 2-D Kohonen map,*
- $rand[a,b]$ *: function furnishing a random number belonging to [a, b],*
- *α: predefined threshold.*

```
-- Map initialisation
$\forall i, j \in [1,n] \times [1,s], w_{ij} = rand[0,1]$

-- Winner selection & kohonen map update
$\forall t_k \in [t_1, t_m]$
    $g(x'(t_k)) = \min_{i \in [1,s]} \| x'(t_k), w_i(t_k) \|$
    $\forall w_i \ni : \| w_i(t_k) - g(x(t_k)) \| < \alpha$
        $\eta(t_k) = \eta_0 \exp(t_k / t_m)$
        $\sigma(t_k) = \sigma_0 . \exp\left(\frac{-t_k \log(\sigma_0)}{t_m}\right)$
        $\pi_{i,g(x'(t_k))}(t_k) = \exp\left(\frac{\|(x'(t_k), w_i)\|^2}{2\sigma^2(t_k)}\right)$
        $w_i(t_{k+1}) = w_i(t_k) + \pi_{i,g(x(t_k))}(t_k) \cdot \eta(t_k)[x'(t_k) - w_i(t_k)]$
```

It is noteworthy that Kohonen algorithm is applicable to large dataset given that (i) the computational complexity scales linearly with the number *m* of samples and (ii) limited memory (i.e., the memory necessary to record the set of training vectors $x'(t_1),\ ...,x'(t_k),...,x'(t_m)$ and the Kohonen map $w_1,...,w_s$. Nevertheless, complexity is quadratic, hence causing a time-consuming training phase. As a 2D-grid, a Kohonen map is of great help for visualising and inspecting the user behaviour recall that the structure of Kohonen map reflects the structure of the original training samples. Based on the trained Kohonen map, which reflects the normal activity of a subject, any deviation from that normal activity can be detected and identified as an anomaly.

3.3 Anomaly Detection

Central to the notion of anomaly detection is the decision threshold. Intuitively, if the distance between the observed and normal behavior is greater than the threshold, then the observed behavior is defined as anomalous. Given our use case - a RFID-enabled control access system attempting to analyze the user location - we distinguish two sources of potential anomalies, the user's position and its trajectory. Intuitively, a position is said to be anomalous if it does not belong to any of the classification defined during the training, i.e., if it does not pertain to any of the clusters centered on the wining neurons defined as part as the training phase (Figure 1 and Algorithm 2).

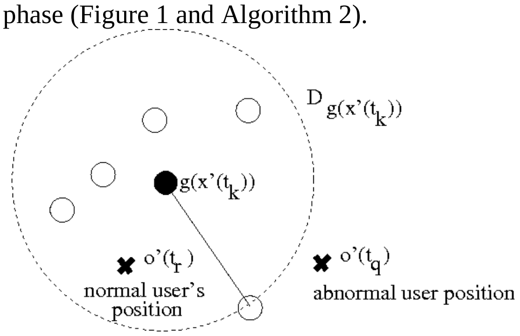


Figure 2. Detection of an abnormal and normal user's position, o'(t_q) and o'(t_r), in a one dimension training set (m = 1) plotted into a 2-dimensional plan: a winning neuron (black circle) is surrounded by some neighboring neurons (white circles) located within a disk (dashed circle).

By extension, we define that a trajectory is anomalous if a great percentage of the user's position is anomalous, i.e., if the pre-processed observation $o'^T(t)=\left(o'_1(t),\ ...,o'_i(t),...,o'_n(t)\right)$ does not pertain to any of the clusters centred around the winning neurons *g (x'(*t_k*))* and circumvented by the radius defined as the maximum distance $\max w_{i\in D_{g(o'(t))}} \left\| g(x'(t_k)-w_i \right\|$ separating the winning node *g(x'(*t_k*))* from its neighbouring neurons, i.e., the neurons that belong to $D_{g\ (x'(tk))}$. By extension, a trajectory *o'(t), …, o'(t+p)* is anomalous if the ratio of anomalous positions exceeds a given threshold defined by *β(r)*.

Algorithm 2. Anomaly detection

Parameters:
Given

- $o'(t),...,o'(t+q),...,o'(t+r)$*: trajectory wherein anomaly is researched,*
- $o'^{T}(t+q)$: *observation obtained a* $t+q$ *,*
  $o'^{T}(t+q)=o'_1(t+q),...,o'_i(t+q),...,o'_p(t+q)$ *with t > t*$_m$
- $g(x'(t_1),...,g(x'(t_k)),...,g(x'(t_k)),...,g(x'(t_m)))$*: set of wining neurons defined during the training phase,*
- α, β:

```
-- Detection configuration
$\forall g(x'(t_k))$ with $t_k \in [1,m]$
        Let $D_{g(x'(t_k))}(\alpha) = \{w_i \ni : \|w_i - g(x'(t_k))\| < \alpha\}$
        Let $= \left| D_{g(x'(t_k))}(\alpha) \right| = \max_{w_i \in D_{g(x'(t_k))}} \|w_i - g(x'(t_k))\|$
-- On detecting an anomalous user's position
$\forall g(x'(t_k))$ with $t_k \in [1,m]$
        if $\|o'(t) - g(x'(t_k))\| < \left| D_{g(x'(t_k))}(\alpha) \right|$
                then o'(t) is normal
                else o'(t) is abnormal

-- On detecting an anomalous user's trajectory
if $\sum_{q=1}^{r}\sum_{k=1}^{m} \mathbb{1}_{\{\|o'(t_q)-g(x'(t_k))\| < |D_{g(x'(t_k))}|\}} < \beta(r)$
        then o'(t), …, o'(t+p) is normal
        else o'(t), …, o'(t+p) is abnormal
```

The computational complexity related to detecting a position and then its trajectory scales linearly the number of winning vectors *g(x'(t*$_k$*))* (bounded by *m*) and with $p \times g(x'(t_k))$ (bounded by *p.m*). In addition to the memory allocated to the training phase, little additional memory (basically, the index *i* of the winning neurons in the Kohonen map and their established radius) is used during the anomaly detection.

4. Implementation and Experiments

In order to assess the proposed solution, we implemented the prototype of an anomaly detector (Figure 1). The overall architecture includes: a RFID system that consists of RFID tags, RFID readers and a back-end database fed by a RFID middleware connected to the readers. In order to detect any anomaly, information provided by the RFID middleware is recorded leading to the creation of a backend database.

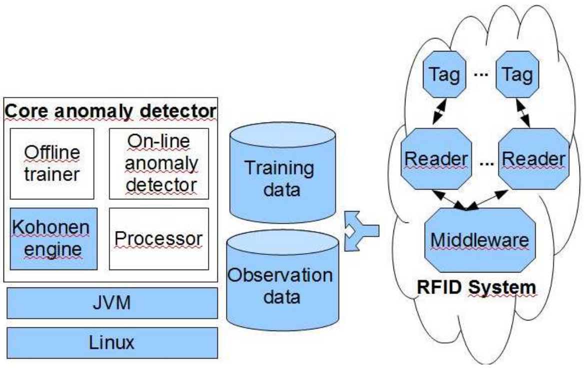
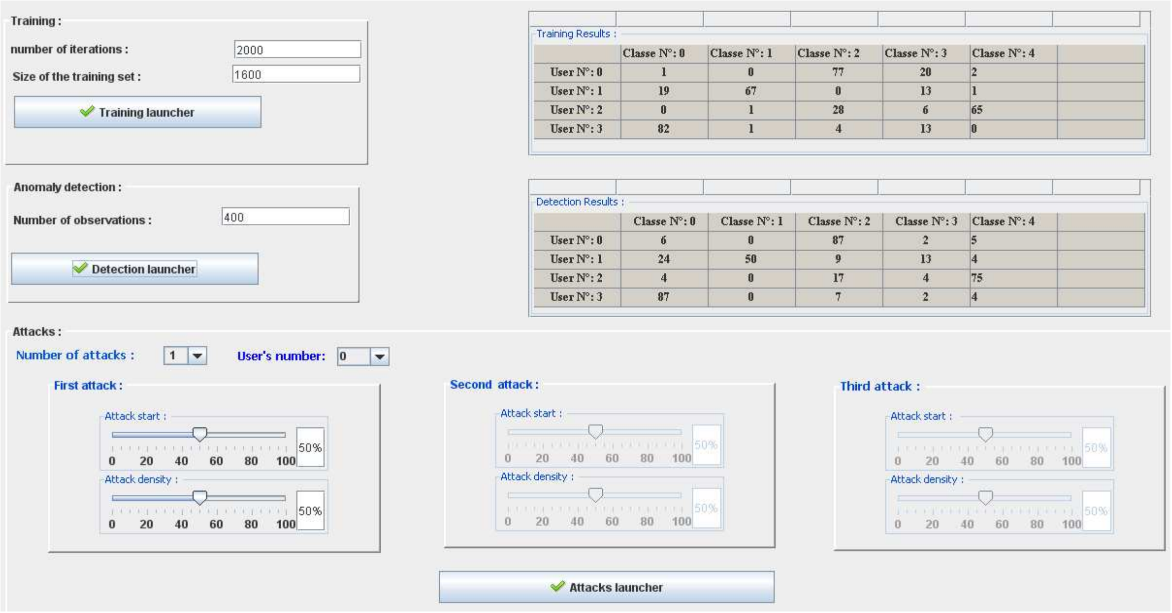


Figure 3. Anomaly detection in a RFID system

For the sake of clarity, we distinguish two backend databases, one devoted to the training and one to gathering observations. Both are constituted of the data collected from the RFID system according to the scenario defined in Section 2, but, their usage differs: the former is used in order to train the anomaly detector whereas the latter serves so as to identify threats. These two activities are performed by the core anomaly detector that can be broken down into:

- A processor which extracts the information from the database in order to parse, filter and normalize it. In practice, data is stored in the database as XML files. The resulting information is then provided either to the trainer so as to build the user's normal behavior or to the anomaly detector in order to detect intrusion attempt.
- A trainer that takes as input the processed training data in order to create a Kohonen Map. This training phase which is performed off-line, permits to classify the user's behavior whereas the anomaly detection is typically performed online, i.e., during the RFID system's run-time.
- An anomaly detection sub-system which identifies abnormal behaviors based on the comparison between the Kohonen Map and the processed samples provided by the RFID system.



Training :

number of iterations : 2000

Size of the training set : 1600

Anomaly detection :

Number of observations : 400

Attacks :

Number of attacks : 1

User's number: 0

First attack :

Attack start : 50%

Attack density : 50%

Second attack :

Attack start : 50%

Attack density : 50%

Third attack :

Attack start : 50%

Attack density : 50%

Training Results :

	Classe N°: 0	Classe N°: 1	Classe N°: 2	Classe N°: 3	Classe N°: 4	
User N°: 0	1	0	77	20	2	
User N°: 1	19	67	0	13	1	
User N°: 2	0	1	28	6	65	
User N°: 3	82	1	4	13	0	

Detection Results :

	Classe N°: 0	Classe N°: 1	Classe N°: 2	Classe N°: 3	Classe N°: 4	
User N°: 0	6	0	87	2	5	
User N°: 1	24	50	9	13	4	
User N°: 2	4	0	17	4	75	
User N°: 3	87	0	7	2	4	

Figure 4. User Interface

The overall anomaly detection system has been developed using Java in conjunction with JVM 1.6, relying on a customized version of the Kohonen engine developed as part as [REN06]. The main goal of this prototype is to prove that the proposed architecture works efficiently on a RFID system. Towards this goal, a simulation of the RFID system was conducted as follows:

- *Step 1* – A self- training-test is generated manually according to the application scenario presented in Section 2. In practice, users' positions are recorded in a XML file.
- *Step 2* – The Kohonen map is trained based on the training record expressed in the XML file,
- *Step 3* – The resulting trained Kohonen map is used in order to detect attack attempts. Towards this goal, a range of anomalies are simulated. In order to facilitate the testing, parameters, e.g., the number of attacks, starting of an attack, degree of density, can be customized through a user interface (Figure 3). In addition, results can be observed using this user interface.

Overall, these experiments are carried on a Windows Dell XPS M 1530, Intel Core 2 duo CPU T5550 1.83GHz, 2 Gb RAM 987 Mhz with the setting up provided in Table 2. The memory footprint of our anomaly detector can be split into 9270Kb for the training component and 318Kb for the detector whereas 6937ms (respectively 250 ms given a trajectory composed of 400 positions) is devoted to the training (respectively anomaly detection).

n	m	s	σ_0	H_0	Measure	α, β
3	1600	400	0.9	0.1	euclidian	4

Table 2. Configuration parameters used during the experiments

We will describe, in the following, the first experiments we have carried out. More sophisticated experiments are planned in a near future. In our scenario, we observe the behaviour of four users during a whole week to produce a normal profile for each one. After the training phase, we obtain the results from the user interface of Figure 4 and we show them more explicitly in Figure 5. According to the results of Figure 5, we can conclude that the normal behaviour of respectively User 0, User 1, User 2 and User 3 is the one representing respectively class 2, class1, class 4, and class 0.

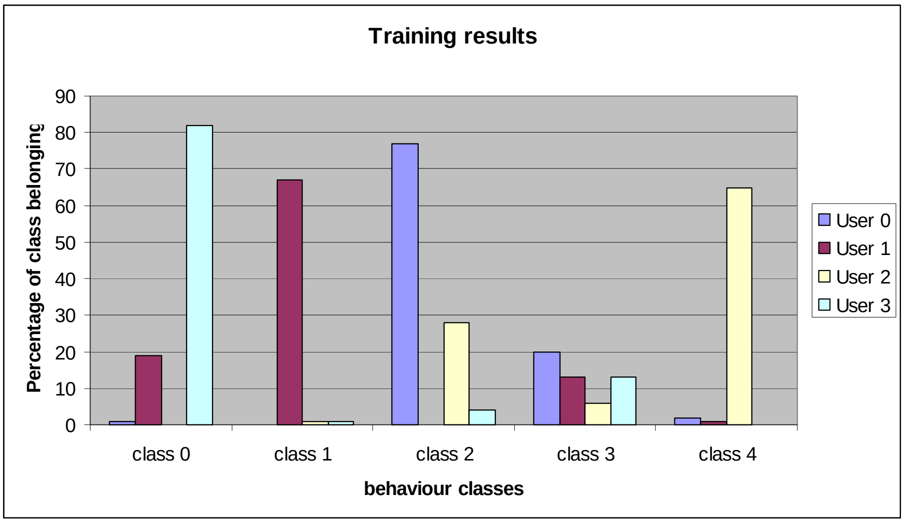


Figure 5. Training results of four users

We decide afterwards to launch on line the anomaly-detection system for a whole day. We obtain the detection results as shown in the user interface of Figure 4. We compare then for each user his/her normal profile with the new one obtained after the anomaly-detection phase. We notice, as in Figure 6, that for each user the deviation does not exceed 25%, which is the threshold that has been fixed in the configuration tool. We conclude consequently that there is no intruder.

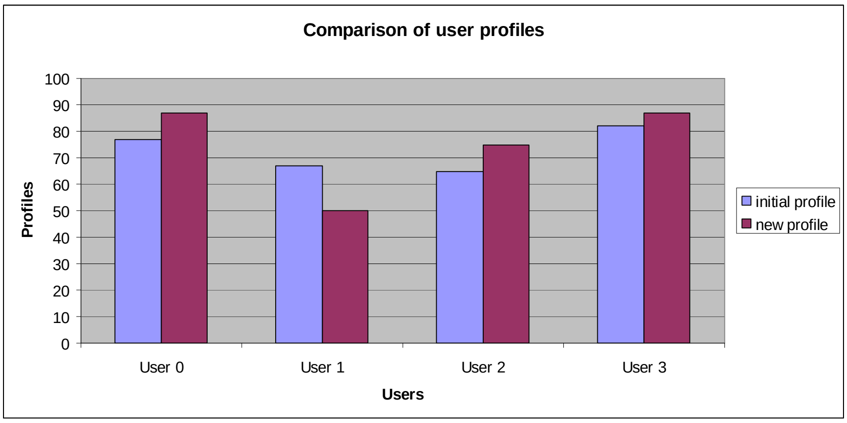


Figure 6. Comparison of user profiles after an anomaly-detection phase

Another day, we allow access to a user that holds the cell phone of User 0 to create an intrusion situation. We launch our system all the day to acquire data during detection phase and to build profiles from these data. According to the results provided by our system, for User 1 to User 3, there was no significant change regarding their behaviour. On the contrary, the profiles of User 0 are significantly distinct as shown Figure 7. In fact, the difference between the normal profile (see class 2) of User 0 and his detection profile is about 30% exceeding the threshold of 25%. User 0 has been viewed by our system as an intruder.

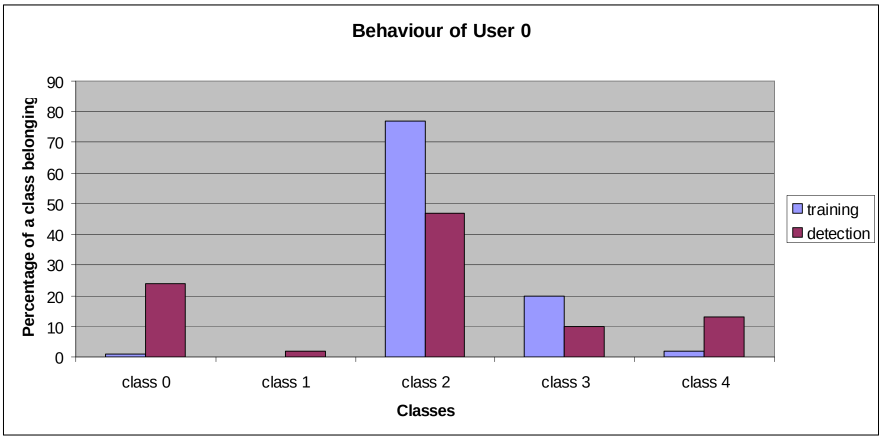


Figure 7. Behaviour of a user imitating User 0

5. Conclusion

In this paper, we propose an anomaly detection system that attempts to find patterns in the data provided by a RFID system, which do not conform to the expected behaviour. For this purpose, we rely on the Kohonen map, a powerful tool for automatically categorising a system activity. In practice, the data provided by the RFID system is first pre-processed in order to train a Kohonen map which permits to define a region representing the normal behaviour of the observed subject. Based on the trained Kohonen map, any activity that does not scope with the defined normal behaviour is identified as an anomaly. The main advantage of this approach is that there is no need for defining the pattern of an intrusion. In addition, such a backend method does not necessitate amending the technical specification of the RFID system. We further developed a prototype of an anomaly detection system which serves as a proof of concept. First experiments show that the time and memory related to the training phase and the anomaly detection together is minimal. We are planning to complement our preliminary simulation-based experiments with real-world tests involving the control access of several computer labs. Such a test bed will permit to obtain real-world traces and their related intrusions and hence constitutes a prerequisite to effectively evaluate the performance of the anomaly detection system in terms of false positive, false negative and number of anomalies effectively detected. We are also thinking in enriching the user profiles with location-, trajectory- and context-related information so as to increase the detection ratio. This enrichment implies extending the core Kohonen engine with novel measures that catch with the heterogeneity of the parameters taken into account in the users' profiles.

Reference

[ABK10] J. Garcia-Alfaro, M. Barbeau, E. Kranakis. Handling security threats to the RFID system of EPC networks. In Security of self-organizing networks: MANET, WSN, WMN, VANET, Auerbach Publications, Taylor & Francis Group, USA, in press.
[BG05] S. C. Bono, M. Green, A. Stubblefield, A. Juels, A. D. Rubin, M. Szydlo.. Security Analysis of a Cryptographically-Enabled RFID Device. Usenix security symposium. pp 1-16, 2005.
[CBK09] V. Chandola, A. Banerjee, V. Kumar. Anomaly detection: a survey. ACM computing survey, vol. 41(3), 2009.
[DE87] D.E. Denning. An Intrusion-Detection Model. IEEE transactions on software engineering, vol 13(2), pp 222-232, 1987.
[EPC07] EPC Global. Class-1 Generation-2 UHF air interface protocol standard Version 1.0.9: “Gen-2”. http://www.epcglobalinc.org/, 2005.
[EV10] M. Esposito and G.D. Vecchia. An ontology-based intrusion detection for RFID system. Tehnological developments in networking, education and automation, 2010.
[LB91] Lo Z.-P. and Bavarian B., “On the rate of convergence in topology preserving neural networks”, *Biomedical Cybernetic*, vol. 65, pp. 55–63, 1991.
[LMF07] M. Lehtonen, F. Michahelles, F. Fleisch. Probabilistic approach for location-based authentication. Technical Report, Auto-ID labs, http://www.autoidlabs.org/publications/page.html, 2007.
[MH07] L. Mirowski and J. Hartnett. Intrusion detection system model to detect change in tag ownership. International journal of computer science and network security. Vol. 7 (7). July 2007.
[MIL06] M.J. Miller. RFIDSim – a simulator for RFID networks, http://mattewjmiller.net/files/rfidsim_doc/html, 2006.
[ML09] M. Langheinrich. A survey of RFID privacy approaches. Personal and ubiquitous computing, vol.13(6), 2009.
[REN06] Rennard J.P. Réseaux neuronaux, introduction accompagnée d’un modèle Java. Book. Published Vuibert Edition, 2006. http://www.rennard.org/irn/som.html.
[TK82] T. Kohonen. Self-organised formation of topologically correct feature maps. Biological Cybernetics vol 43(1), January 1982.
[TS08] G. Thamilarasu and R. Sridhar. Intrusion Detection in RFID Systems. IEEE Military communication conference (MILCOM), Januray 2008.
F. Kerschbaum and N. Oertel. [Privacy preserving pattern matching for anomaly detection in RFID anti-counterfeiting. 6th workshop on RFID security, 2010
[WS04] S.A. Weis, S. E. Sarma, R.L. Rivest and D. W. Engels. Security and privacy aspects of low-cost radio frequency Identification Systems.. In Security in Pervasive Computing, Vol. 2802, pp. 201-212, 2004.
[YGD10] H. Yang, J. Guo and F. Deng. Collaborative RFID intrusion detection with an artificial immune system. Journal of intelligent information systems, Springer, pp 1—26, 2010.