Gesture detection of passive RFID tags to enable people-centric IoT applications

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***Abstract*—Our society may enhance and create new services in a people-centric IoT context through the exchange of information with sensor devices. Unfortunately, attackers might compromise the communication and current intelligent objects with sensor capabilities, are expensive (i.e. smartphone). Within the technologies involved in the IoT paradigm, passive Radio Frequency Identification (RFID) allows the inventorying of simple objects towards a wireless communication with a low-cost investment. We present a solution to increase the security in quotidian tasks (e.g. accessing a restricted area with a contact-less card) by identifying people-object gestures with a passive RFID tag. We demonstrated the feasibility of our proposal by detecting the 95.3% of people-object gestures. As a future task, we aim to implement it in a real scenario.**

***Index Terms*—RFID, Security, Movement recognition**

I. Introduction

OUR society has been living connected from centuries. At first, among them as individuals (i.e. face to face conversations) and later through computers like on the Internet. Currently, the *object* entity has become part of the connection with people, the well-known Internet of Things (IoT) paradigm. The IoT enhances and increases the interaction with entities obtaining rich information for future services where humans become the center of the interactions. From smartphones to wearables, people carry sensors that can enable people-centric services and applications within the IoT context.

Within the different commercially available IoT technologies, Radio Frequency Identification (RFID) enables identification and personalized services by means of a simple electronic label and a reader system. RFID automatizes services such as accessing to restricted areas or identifying an individual in a purchase transaction, by means of simply interacting with the RFID system. The benefits of such systems may, nonetheless, come together with drawbacks. These interactions may be compromised due to a number of factors like unreliable communication, the IoT inherent complexity, or security threats like impersonation or spoofing. For instance, if an attacker obtains the IoT-enabled object identity (i.e. an RFID card identification), the security will be compromised since the attacker will be able to impersonate the legitimate user.

The fact that IoT provides not only connectivity or identification, but a large range of features, may provide a solution to the above problem. For instance, the RFID technology not only provides the unique identification of a given object. It also generates other relevant information such as timestamps, localization and low-level radio frequency indicators. For instance, Received Signal Strength Indicator (RSSI), or phase (PHASE), may reveal further information such as distance, movement, or interaction with people. Moreover, RFID-tags can also include sensors like temperature, pressure or accelerometers. Thus, besides the identification code, other RFID-related features can be used to personalize IoT interactions.

In this paper, we present a method for gesture detection using passive RFID tags to enable people-centric IoT applications and services. The goal is to enhance security by means of classifying specific gestures using a passive RFID tag with a battery-less accelerometer sensor embedded to it. Specifically, we achieve the following contributions:

- A method to characterize the people-object gestures based on acceleration time-series information
- The implementation of an unsupervised machine learning techniques to classify people-object gestures
- An evaluation of the classification of people-object gestures with off-the-shelf devices and equipment

The remainder of this paper is organized as follows: Section II details the problem motivation and the related state of the art. The RFID-based people-object gesture detection principle is described in Section III, and Section IV presents the methodology and experimentation procedure to collect and classify the people-object gestures. We empirically evaluate the people-object gestures in Section V. Finally, the paper is concluded in Section VI, also pointing out future work directions.

II. Related Work

Daniels et al. [1] recognize hands movements by using two cameras and a middleware to extract the information of the frames. Although they obtained a high performance solution, this approach is expensive both economically and computationally. Ali et al. [2] extract biometric data thanks to a video surveillance system, and by using the Distance Based Nearest Neighbor Algorithm a given hand movement can be verified. However, it also requires expensive video surveillance systems. By using sensor equipment, Mare et al. [3] present a solution correctly identifying 85% of the users. They use a bracelet with an accelerometer and gyroscope to compare the motion information with the groundtruth. In case of security and safety for people with motion diseases, Gonçalves et al. [4] propose two approaches to detect undesired body motions. The first approach uses the Microsoft sensor Kinect and gesture recognition algorithms, and the second approach uses a trademark device of Texas Instruments with built in accelerometers and statistical methods to recognize stereotyped movements. A movement recognition device attached to the arm with an accelerometer and EMG sensors is implemented by Shin et.

al [5]. Flores et al. [6] introduce a low-cost wireless glove controller detecting finger gestures, developed using makeshift flex sensors and a digital accelerometer. A signaling approach is presented in Björklund et al. work [7]. They can classify human targets by comparing micro-Doppler signatures using a 77 GHz radar.

Different authors tried to address the challenge of classifying human gestures using RFID technology. A glove equipped with accelerometer sensors and an RFID reader is presented in Hong et al. work [8]. Although these solutions show good results in detecting hand movements, they require sensors fed with a battery, besides being obstructive. Wartha and Londhe [9] introduce the topic of people verification through a basic movements with an RFID labeled-object. Parada et al. [10] presents a method for classifying an object between being static and interacted, in context-aware smart shelf scenario, by uniquely using RFID data. Asadzadeh et al. [11] proposes the recognition of gestures using three RFID antennas distributed within a limited matrix and classifying the movements using a hypothesis tree method. **Although these approaches of gesture recognition by using RFID returned promising results, they detect simple gestures or require of multiple antennas. We propose the recognition of spatial gestures using a single antenna and a battery-less passive RFID tag with accelerometer sensor capabilities.**

III. RFID-BASED PEOPLE-OBJECT MOVEMENT DETECTION

Within the different RFID technologies and standards, the UHF EPC Gen2 [12] RFID is a *de facto* standard in retail. In EPC Gen2, RFID antennas interrogate in a time-multiplexed manner to RFID passive tags, and these RFID passive tags within the read range backscatter the signal back to the RFID reader. The RFID reader not only can inventory those RFID tags within its read range, but high and low-level indicators are included in the backscattered signal. High-level indicators such as the identification code, timestamp, antenna port and reader identifier can also be obtained.

The high-level indicators uniquely identify an object within the object population, besides providing an implicit timestamp for each sample. The low-level indicators provide an approximated measure of the radio frequency signal in the tags as measured by the RFID antenna. The RSSI is modeled by the two-way radar equation for a monostatic transmitter, while the PHASE is approximated by the combination of the round trip distance between the reader's antenna and the tag, plus the phase rotation introduced in the transmission, reception and at the tag itself.

- High-level indicators
  - Identification code (96-bit typically)
  - Timestamp
  - Antenna port
  - Reader identifier
- Low-level indicators
  - Received signal strength indicator (RSSI)
  - Radio frequency phase (PHASE)

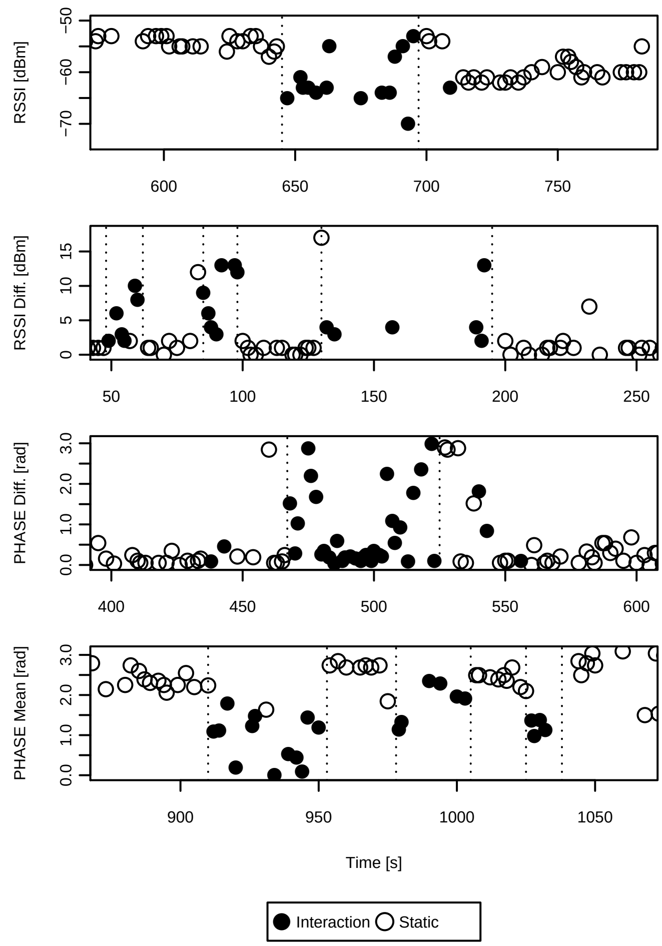


Fig. 1: RFID low-level indicators like RSSI and PHASE may describe object movement, which can be inferred as interaction with persons.

The intuition behind a people-object movement is given by a variation on the low-level RFID indicators. Detecting weaker RSSI and unstable PHASE samples imply a longer coarse grained distance between tag and antenna. Opposite, a tag returning stronger RSSI and stable PHASE samples imply a static tag [10]. Figure 1 shows the variation of RFID features in a dynamic movement (i.e. interaction) represented with black dots. Opposite, if the object remains static the values remain constant as indicated with white circles.

Nevertheless, RFID low-level signals only allow to detect coarse movements like people-object interactions, but not fine grained movements like user's gestures. Thus, detecting specific gestures require further context-aware information. A solution improving movement detection accuracy, within the same passive RFID technology is integrating sensors in the RFID labels. For instance, accelerometers have been demonstrated as reliable sensors to detect fine-grained movements [6], [8]. An accelerometer detects movement through the spatial coordinates x, y and z with respect to the gravity (measured in m/s^2 or g), generating a time-series of movement-related data.

Next, we detail the proposed methodology to detect specific users' gestures by using passive RFID tags with an integrated accelerometer sensor.

IV. Gesture-Detection Methodology and Experimentation

This paper aims to classify people-object gestures with a battery-less accelerometer sensor embedded in a passive RFID tag enabling people-centric services and applications while improving security in the IoT context. For instance, authentication in a restricted area access, or authorizing payments in a commercial transaction. The goal is to combine the implicit RFID authentication with a specific gesture, providing two levels of authentication and reducing security threats from third entities like spoofing.

Figure 2 summarizes the methodology used to enable gesture classification. Specific gestures are performed using a passive RFID tag with accelerometer sensor capabilities, and a state-of-the-art smartphone with an integrated accelerometer for comparison purposes. The gestures data is sampled by commercial RFID equipment (RFID antenna and reader, connected to a computer) for the RFID label, and using a specific application for the smartphone. The data is stored as a collection of time-series information. To enable further analysis, a preprocessing stage is applied dividing the time series into individual gestures, also filtering static periods before and after the actual gesture. Feature extraction is enabled by using the *Dynamic Time Warping* (DTW) algorithm [13], which measures the similarity between two time-series resulting in a numeric distance. The lower the numeric distance the higher the similarity between the two time-series is. Thus, DTW is used to extract the distance between each performed gesture by either the passive RFID tag and the smartphone. Finally, an unsupervised machine learning algorithm is used to classify the time-series blocks and predict the input gesture. Because its simple implementation and robustness with respect to the spatial distribution of the samples, *k-nearest neighbor* (kNN) [14] is used in our experiments. In the kNN algorithm, the parameter k indicates the number of nearest neighbors a test sample is compared to, classifying based on the majority of votes. For instance, if a test sample is compared with the 4 nearest neighbors and three of them are class A, this test sample will be considered also as A class.

The procedure of people-object gesture classification is based on performing a given gesture action with both the passive RFID tag and the smartphone. In the experimentation stage, we used commercial RFID equipment including a passive tags with an integrated accelerometer from the company Farsens [15], and a commercial smartphone equipped with Arduino. We defined three different gestures which we denote as: *R*, *W* and *C*. Figure 3 shows three images corresponding with the procedure of people-object gestures. The image 3a represents the initial position before complying a given movement. Images 3b and 3c correspond with the movements *W* and *R*, respectively. The intuition behind the people-object gestures is given by the variation of the three time-series accelerometer data associated with each of the spatial coordinates x, y and z. Figure 4 shows the spatial coordinates x, y and z with respect to the time, while the passive RFID tag with accelerometer sensor capabilities is performing a *C* gesture on the space. We can observe how the spatial coordinates varies during the dynamic action.

Specifically, a total of 30 samples were performed, half with the passive RFID tag and the other half with the smartphone. With each device, we executed the three predetermined gestures *R*, *W* and *C*. Since each gesture is composed of three time-series (one for each spatial coordinate), a total of 90 time-series were generated in the experimentation stage. Therefore, a matrix of 2700 distances is generated by comparing each time-sequence representation to the rest.

V. Evaluation and results

IoT-based gesture detection in the context of people-centric applications and services must offer a proper performance in order to improve authentication and security. Hence, gestures classification performed on either passive tags and smartphones must be accurate and reliable. Next, we present the evaluation of the experimental work introduced in the previous section. As described in the Section IV a total of 2700 time-series are generated from the 30 executed tests. 10-fold cross validation is used to evaluate the kNN clustering based on DTW features. kNN is in turn evaluated using 10, 8, and 5 samples for parameter k.

The table I tabulates the ratio of the people-object gesture's classification from both the passive RFID tag and the mobile device. The total number of 30 samples of movements, are divided in each of the three movements *C*, *R* and *W* and for each device. In addition, the ratio is calculated based on the number of neighbors (k). For each value of k the classified gesture with highest ratio, together with its ratio are shown.

From the results, it is possible to see how the movement *C* is predicted correctly from both passive RFID tag and mobile device for all k values. Similar occurs with the movement *W* where only predicts the wrong movement with the passive RFID tag setting the k value to 8. Opposite, the *R* movement seems more difficult to predict with the passive RFID tag where only with the k values 5 and 2 the right prediction is obtained. As a general comment, the mobile device provides the highest rate of predictness right. And, the k values 5 and 2 returns higher ratio of rightness being that last the best. Since the mobile device returns almost a 100% of rightness prediction on recognizing the performed gestures, we aim to evaluate deeper the battery-less passive RFID tag.

Besides the ratio of prediction, we calculated the metrics measurements: Precision, Recall, F-score and Accuracy in based on the statistical classification using the well-known confusion matrix. Figure 5 shows the percentage (y-axis) for each measurement metric with different k values (x-axis). The input of samples correspond with the one extracted from the passive RFID tag uniquely.

As we can observe in the Figure 5 with k values of 10 and 8, we obtain the same metrics results. However, when this value decreases the measurement metrics increases. With a k value of 2, the accuracy of the system reaches the 93%.

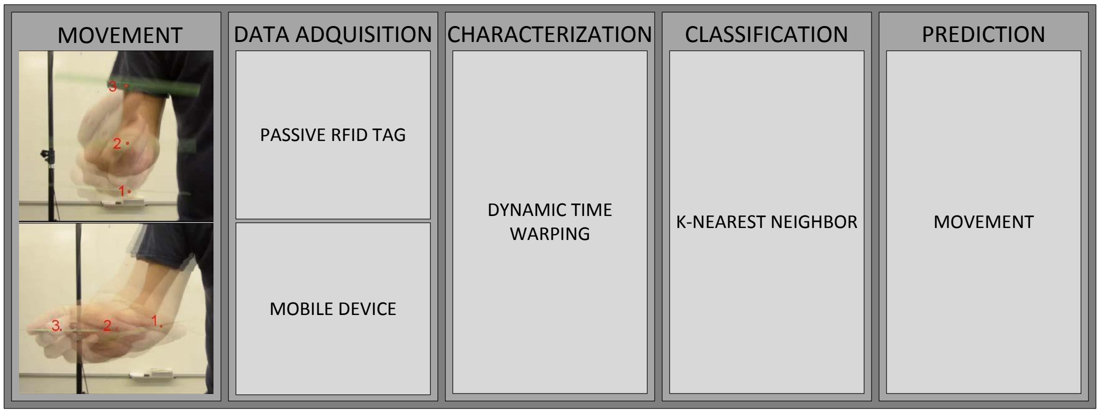
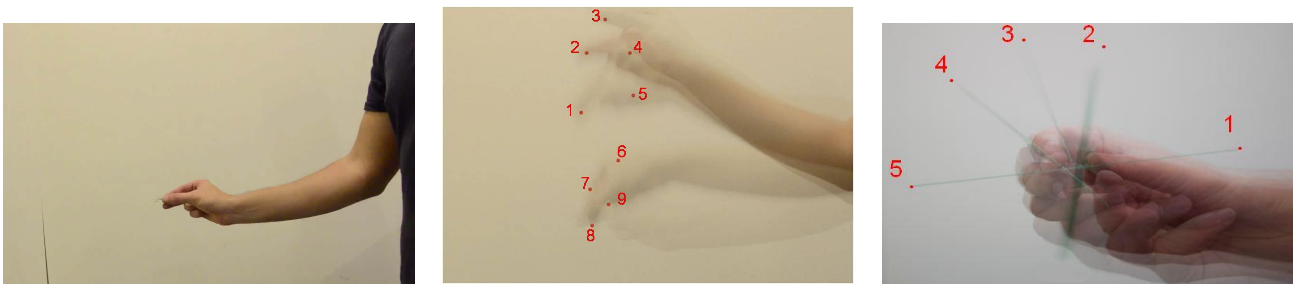


Fig. 2: People-Object movement classification scheme.



(a) Initial position

(b) W movement

(c) R movement

Fig. 3: Movement

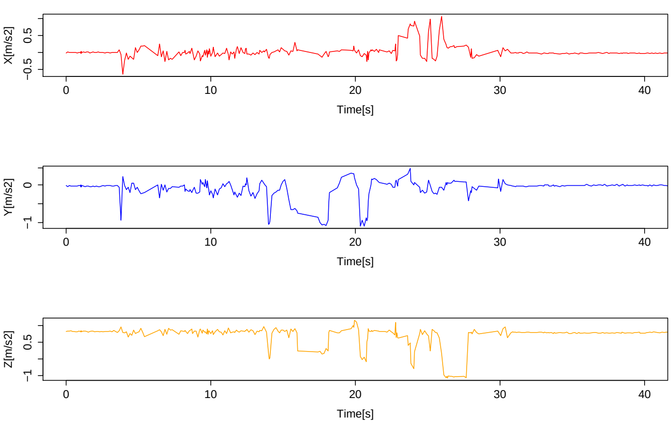


Fig. 4: Each gesture generates three time-series, one for each spatial coordinate. Here, the C gesture is shown.

Indeed, the results confirm our hypothesis demonstrating the feasibility of our solution to detect people-object gestures using a mobile device and a passive RFID tag in a People-Centric IoT paradigm to increase security in quotidian tasks.

TABLE I: Ratio of people-object gestures' predictions

Sample [#]	Movement	Device	Prediction / Ratio			
			k=10	k=8	k=5	k=2
1	C	Passive RFID tag	C / 0.7	C / 0.75	C / 0.8	C / 1
2			C / 0.6	C / 0.75	C / 0.8	C / 1
3			C / 0.5	C / 0.5	C / 0.8	C / 1
4			C / 0.6	C / 0.75	C / 0.8	C / 1
5			C / 0.8	C / 0.75	C / 0.8	C / 1
6		Mobile	C / 0.6	C / 0.625	C / 1	C / 1
7			C / 0.8	C / 0.875	C / 0.8	C / 1
8			C / 0.8	C / 0.875	C / 1	C / 1
9			C / 0.9	C / 0.875	C / 1	C / 1
10			C / 0.8	C / 0.750	C / 1	C / 1
11	R	Passive RFID tag	C / 0.7	C / 0.625	R / 0.6	R / 1
12			C / 0.7	C / 0.625	R / 0.6	R / 1
13			C / 0.7	C / 0.625	R / 0.6	R / 1
14			C / 0.6	C / 0.5	R / 0.8	R / 1
15			C / 0.6	C / 0.625	R / 0.6	R / 1
16		Mobile	R / 0.5	R / 0.625	R / 0.8	R / 1
17			C / 0.5	R / 0.625	R / 0.8	R / 1
18			R / 0.5	R / 0.625	R / 0.8	R / 1
19			R / 0.5	R / 0.625	R / 0.8	R / 1
20			R / 0.5	R / 0.625	R / 0.8	R / 1
21	W	Passive RFID tag	W / 0.5	C / 0.5	W / 0.8	W / 1
22			W / 0.7	W / 0.75	W / 0.8	W / 1
23			W / 0.7	W / 0.625	W / 0.8	W / 1
24			W / 0.8	W / 0.750	W / 0.8	W / 1
25			W /0.9	W / 1	W / 0.8	W / 1
26		Mobile	W / 0.7	W / 0.875	W / 1	W / 1
27			W / 0.7	W / 0.875	W / 1	W / 1
28			W / 0.7	W / 0.875	W / 1	W / 1
29			W / 0.7	W / 0.875	W / 1	W / 1
30			W / 0.7	W / 0.875	W / 1	W / 1

VI. Conclusion

In a People-Centric IoT paradigm, objects enhance the communication in a Smart City context by improving or creating new services. Nevertheless, this exchange of information may be corrupted by third parties, compromising the security between entities. The RFID EPC Gen2 allows a

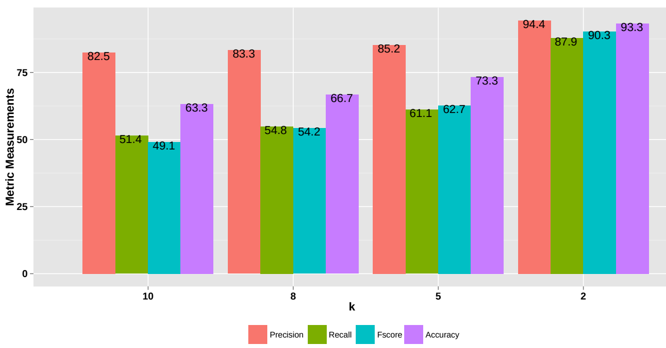


Fig. 5: The highest metrics is achieved with k=2.

non-line-of-sight communication with low-cost passive RFID tags.

The results demonstrated the suitability of our proposal by predicting the executed People-Object movement using the smartphone and a passive RFID tag. The best value of nearest neighbors is 2 (k) from both the mobile device and the battery-less passive RFID tag. Thus, we obtain a double security by only performing people-object gestures from those elements.We envision a society in a People-Centric IoT paradigm where the people are safer on performing quotidian actions such as entering restricted areas or confirming bank payments with the smartphone and battery-less devices efficiently.

We plan to implement our solution in a real scenario. Our future work includes, but is not limited to:

- Extract the RF information from the passive RFID tags to extrapolate the experiments
- Perform more experiments with different movements
- Study other unsupervised machine learning techniques to increase even more our output
- Evaluate our proposal in other People-Centric IoT context situations like motor neuron disease.
- Implement a real time application to be used in a People-Centric IoT context

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