# Measuring User-Object Interactions in IoT Spaces

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***Abstract*—Online commerce currently provides better customer activity information, compared with traditional retail stores. For instance, measuring customers' interest on products in shelves is a complex task in physical environments. However, these scenarios may benefit from the Internet of Things (IoT) technologies to obtain context-aware information hard to obtain otherwise. For instance, in a real store, users may show their interest in a given product depending on the time interacted with it. We present a system designed to reliably detect user-object interactions in an RFID-enabled context-aware shelf scenario, with the goal to measure user activity based on the weighted Information Gain classifier (wIG), an empirical machine learning technique. The system is configured by means of thresholds determining the classification accuracy, and it is automatically adapted to different scenarios by means of an automated calibration method. Our proposed user-object interaction measurement method achieves performance above 80% in a real environment evaluation, indicating a high reliability. Our proposal could be used to feed user-centric privacy-preserving recommender systems in brick-and-mortar stores, or as aiding tool for visually impaired users.**

## I. Introduction

Nowadays, more and more retailers use technology to increase their business. The Internet of Things (IoT) technologies, where context-aware connected devices are deployed in almost every physical scenario, are increasing worldwide and could impact on retail scenarios' benefits [1]. Within the different commercially available IoT technologies, Ultra High Frequency (UHF) Radio Frequency Identification (RFID), defined in the Electronic Product Code Class 1 Gen2 (EPC Gen2) [2], is *de facto* standard in retail. Many retailers already attach UHF RFID tags to their products [3], to monitor stock or speed up cash processes [4].

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 indicators such as Received Signal Strength Indicator (RSSI), or radio frequency phase (PHASE). The passive RFID tags allow physical objects to communicate in IoT scenarios, with the raw data provided by the RFID technology being an advantageous information to develop smart systems within the IoT scenario. This ubiquitous computing scenario can make use of the RFID information stream to enable Business Intelligence by means of data mining and machine learning techniques. We can envision a person shopping, receiving additional information in her smartphone about a product (without the need of revealing personal data) by only taking it from the shelf. Furthermore, sellers could benefit from the information about all the user-object interactions taking place within the store if presented in a comprehensive way for them.

The overall goal is to improve user's shopping experience by reliably detecting in real time user-object interaction in an unassisted manner, uniquely by means of RFID information. Specifically, we achieve the following contributions:

- An empirical supervised classification technique designed to measure user-object interactions in a physical scenario
- An autonomous calibration method to provide real-time ground truth feedback to the user-object interaction classification system
- An scalable and low-cost prototype of our proposed system, equipped with off-the-shelf IoT 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 interaction detection principle is described in Section III, and Section IV presents our proposed wIG classifier for a context-aware shelf to detect user-object interactions. We empirically evaluate the wIG algorithm in Section V. Finally, the paper is concluded in Section VI, also pointing out future work directions.

## II. Related Work

Customer related data are gaining more and more importance for retailers to drive their business even more consumer oriented [5]. Indeed, extracting information about user's online browsing (web analytics) is a multi-billion dollar business today [6]. However, still most purchases occur in physical spaces, and in these scenarios, loyalty programs are the main source of customer satisfaction data. Unfortunately, these programs do not give information about the shopping process which would be of utmost importance to improve customer satisfaction. Thus, one challenge that needs to be addressed is how to extract data from the shopping process in physical stores in a privacy-preserving manner.

With this objective in mind, the first problem that needs to be solved is the detection of user-object interaction (also referred as user-product interaction in the retail context). This is a well known research area in fields such as computer vision. However, computer vision approaches have important drawbacks, being the implementation complexity, and the difficulty to differentiate similar objects, the most important ones. In recent years, ubiquitous computing technologies such as IoT, and more specifically RFID, have been introduced to try to address this issue. However, RFID is usually used as a simple identification platform, while activity information is extracted from battery enabled sensors [7] (accelerometer, gyroscope, etc.) or computer vision [8].

RFID data as the main source for information extraction is also present in the literature. [9] presents an interesting work on extracting users' interest from book-browsing behaviors recorded with RFID. Unfortunately, they focus on the books' keyword extraction and classification and the RFID system is not detailed. Furthermore, the system judges a book has got picked up from the shelf only if the book is taken farther from the shelf than 50 cm. A wine recommendation system is described in [10] where RFID is also implemented. In [11] and [12] the false positive reads problem is explored, statistically analyzing whether reading patterns from different objects and antennas comply with predefined retail operations. Huiting et al. exploit phase measurements of EPC Gen2 tags for localization and movement detection [13]. Keller et al. [14] propose a machine learning based approach that makes use of the low-level RFID reader data to detect false positive reads in a scenario with static labeled objects such as a factory or a distribution center. Finally, Li et al. propose in [15] a method to detect gesture recognition based on UHF RFID.

Opposite to [8] and [7], our approach to analyze user-object interaction is based on RFID measurements and the ground truth provided by sensors, which simplifies and reduces its cost in a real implementation. Besides the actual high-level inventory information, we use multiple low-level RFID indicators such as received signal strength indicator (RSSI) and RF Phase (PHASE) to improve resolution on the user-object interaction. Our approach differs to Weiss-Ferreira-Chaves et al. [11] and and Keller et al. [14], which classify based on single indicators and static tags, while this paper applies similar and improved principles to the retail space in order to detect dynamic tag movements indicating consumer-object interaction.

## III. RFID-based Interaction Detection Principle

In this section, we describe our approach on detecting user-object interaction in an unassisted and scalable IoT scenario. Based on [16] work, where the basic classification principle is described, we present a low-cost and deviceless (from the user perspective) user-object interaction detection method allowing better scalability and improved classification metrics. By means of RFID and sensors, the system is automatically trained enabling unassisted supervised classification. That is, with the regular user-object interactions performed by costumers or employees.

### A. Using RFID Indicators to Reason Interaction

EPC Gen2 is a low-cost Ultra High Frequency RFID technology. Labels are the largest element within the RFID system, since there are much more labels than readers or antennas. Hence, EPC Gen2 is considered low-cost RFID because the labels' cost is usually below 5 cents of Euro. EPC Gen2 tagged objects are constantly interrogated by the antennas of an RFID system on a time-multiplexed basis. That is, each antenna interrogates the tag population in its area during a *reading time*, after which the next antenna repeats the same procedure. Typical *reading times* are about a hundred to few hundreds of milliseconds. Since the interrogator emits electromagnetic signals to all reachable passive RFID tags, those backscatter with their ID and other information such as RF indicators and timestamp. Each tag sample obtained by a state-of-the-art commercial RFID system is composed of high and low-level RFID indicators, the following being the most relevant:

- 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)

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 [17].

The intuition behind the user-object interaction detection is given by a variation on the low-level RFID indicators. Detecting weaker RSSI samples imply a longer coarse grained distance between tag and antenna, while PHASE variance may detect fine-grained changes in the tag position (see [13] for more details on UHF RFID PHASE extraction). Opposite, a static tag returns stable low-level measurements.

### B. Data pre-processing into features

As first step in our method, the indicators described above are used to model a set of ten high-level features whose goal is to describe variations in the tag position (i.e. interactions with users). Table I describes the features used in our method.

Modeling tag-position variations is achieved by combining three groups of features including raw values as returned by the RFID system (1, 2, 3), difference of consecutive values (4,5), and statistical measures of samples sets during $n$ *read times* depending on the number of antennas used in the RFID system (6 to 10). Figure 1 depicts four features examples obtained by different RFID antennas, of about 200 seconds length at different temporal windows. In each example, one or more interactions with different lengths are recorded for a single labeled object. Solid points represent interaction samples and empty points represent samples where the object was static and remained at the same place. Notice that a few errors are recorded due to sensors misbehavior.

### C. Scalable and automated ground truth extraction

The interaction features mentioned above are mainly based on radio frequency indicators, and thus, strongly influenced by the physical environment. Hence, the feature's actual values may significantly vary with the environment (i.e. the shelf material, tag-antenna distance, electromagnetic interference, etc.). To overcome this issue, we propose to collect ground truth from a subset of tags using sensors, to improve learning on the actual activity in a given scenario. Looking for a simple solution to keep low complexity and cost of the system (for the sake of implementability in a real scenario) we propose the utilization of simple sensors like Light Dependent Resistor (LDRs), or infrared proximity LEDs, behind the labeled objects. A threshold, then, determines the object's state. For instance, if a LDR does not receive light, it is assumed that the object remains static. Opposite, if the sensor receives light, it is considered that the object has been taken off the shelf.

Despite the reliability of this ground truth method, only a binary presence/absence state is obtained. However, the RFID features return a richer information set on the labeled objects activity since they can be tracked even on users' hands. Notice that to train the system, it is not necessary to get ground truth information from all the objects, but a number of them to allow supervised training. The collected ground truth information is only used in our proposed method to train in real time a classifier fed by the RFID-based features. Although the LDR sensors detect objects presence or absence, those cannot identify the interacted object. However, the RFID system identifies each labeled object regardless of its relative position with regard of the antennas.

### D. Data Calibration

The LDR sensors are used in our system to automatically calibrate the RFID samples recorded by the antennas. If all LDRs receive light, the system assumes all objects are present in the shelf. The opposite state is recorded during

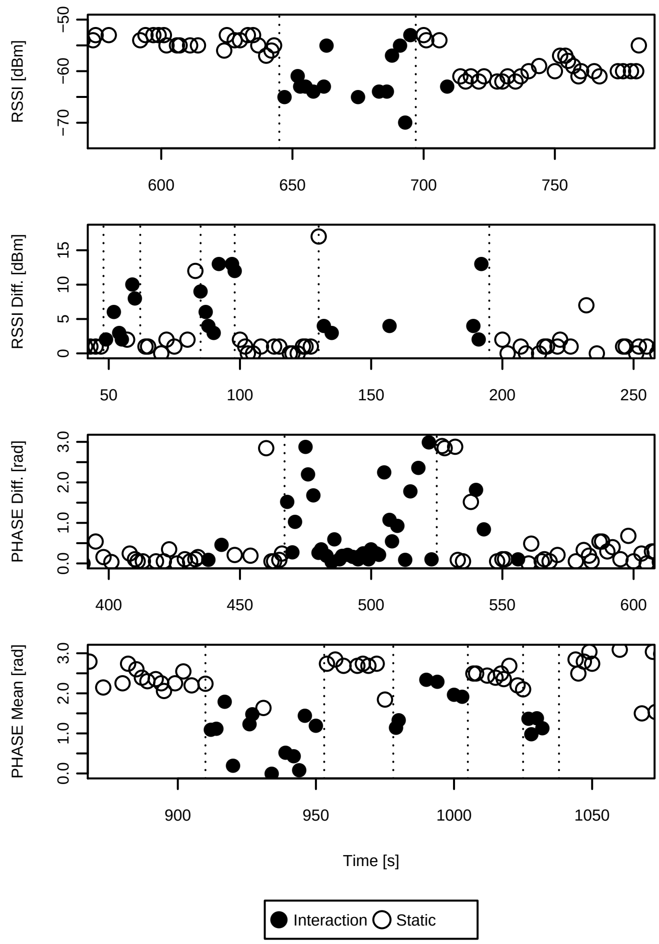


Fig. 1. RFID indicators like RSSI and Phase may describe object movement, which can be inferred as interaction with persons. Interaction and static samples in this figure are automatically determined by an LDR sensor.

interactions. The procedure of interaction is done as occurs regularly. A costumer takes a tagged-item from the RFID-enabled shelf, and holds it up during an unspecified amount of time ranging from one second to more than one minute. After the interaction, the customer optionally can return the tagged item back to the shelf. During the interaction time the tagged-item is still sampled by the RFID system but an LDR is receiving light, thus, recording an interaction. Based on this behavior, all samples are labeled as static or interacted, allowing the data calibration.

Calibration time depends on the classification method and samples distribution. Nevertheless, once an interaction is performed, the system is able to run. The larger the number of interacted samples, the better the classification metrics.

TABLE I
SUMMARY OF THE THREE GROUPS OF FEATURES MODELING INTERACTION BASED ON RFID DATA.

| |
|---|
| **1 - RSSI:** Reader's measurement of the backscattered power from the tag. |
| **2 - PHASE:** Reader's measurement of the phase rotation from the tag. |
| **3 - READ COUNT:** Number of samples from a same tag within a single *read time*. |
| **4 - RSSI DIFF:** Absolute value of the difference of a given RSSI value and the previous sample. |
| **5 - PHASE DIFF:** Absolute value of the difference of a given RF Phase value and the previous sample. |
| **6 - RSSI MEAN:** Mean of RSSI samples within $n$ *read times* |
| **7 - RSSI STD:** Standard deviation of RSSI samples within $n$ *read times* |
| **8 - PHASE MEAN:** Circular average of PHASE within $n$ *read times* |
| **9 - PHASE STD:** Circular standard deviation of RF Phase samples within $n$ *read times* |
| **10 - READ TAG/ANTENNA:** The number of antennas detecting a single tag within $n$ *read times* |

## IV. wIG ALGORITHM PRINCIPLE

We propose an empirical supervised machine learning technique, the weighted Information Gain classifier (wIG). It has been developed in order to solve the problem of automatically detecting user-object interactions in an RFID-enabled context-aware shelf scenario. The wIG algorithm is based on the

Information Gain (IG) algorithm [18] also known as the Kullback-Leibler divergence. Opposite to standard machine learning techniques like Support Vector Classifier, Random Forest (tree-based) or Logistic Regression, the wIG algorithm is empirically designed to fit in a context-aware RFID-enabled shelf scenario. Readers interested into further details on wIG comparison with standard state-of-the-art machine learning techniques can refer to [19].

### A. Information Gain Algorithm

We propose a classification method which predicts two event types, static or interaction. Our system collects RFID-based data from user-object interactions and by implementing LDR sensors as a ground truth, samples can be classified. Our proposal is based on the Kullback-Leibler divergence (or Information Gain) [18]. It measures how distant two probability distributions are, or in our case, how well two event types can be separated depending on a specific threshold:

$$\mathrm{IG}(t,f) = H(t) - \left[\frac{|t \leq \theta|}{|t|} H(t \leq \theta) + \frac{|t \geq \theta|}{|t|} H(t \geq \theta)\right]$$

The above equation formulates the Information Gain (IG) where $H$ defines the samples entropy for samples $t$; $\theta$ defines the thresholds used for classification, and features are represented as $f$.

Our proposed method is based on a preliminary model described in [16] where the authors fitted their approach by using the mentioned Kullback-Leibler divergence to classify the two event types as static or interacted tagged-object and applying a Bayesian Noisy-OR Network to reason interaction. Opposite to Melià-Seguí and Pous work, the ground truth in our approach, necessary for enable supervised learning, is obtained through automated LDR sensors sampling.

### B. Classification's procedure

The basic wIG classification principle is based on applying the IG algorithm to each set of tag-features-antenna samples. The classifier starts without any information (cold start). Once the RFID reader initiates the identification rounds, all tags within the reading range will send data to the reader, through the reader antennas. That is, each tag response is sampled by one specific antenna. These data is organized into features in the information systems (IS) back-end. Additionally, a number of LDR sensors continuously sample the objects presence/absence, providing groundtruth data. Finally, the IS merges and calibrates by means of timestamps both information sources, allowing the classifier to perform supervised learning by applying 10-fold cross validation on the obtained data samples.

Once the IS begins to receive both static and interacted samples, the system generates an IG value for each set of tag-feature-antenna. The larger the IG value for that set of samples, the better the classification, based on a threshold $\theta$. The wIG classifier then filters the results based on two thresholds defining the minimum IG values to consider a correct classification, and the minimum number of features returning correct classifications. The Equation below summarizes wIG's operation.

$$\mathrm{wIG}(a_l, t_m, f_n) = \max_{\theta_n} \{\mathrm{IG}(t_m | a_l, f_n)\}$$

The wIG's goal is to provide classification fine tuning. Better classification is achieved at the expense of considering only those set of samples with higher IG values, with the associated risk of losing actual interactions. By decreasing the thresholds, more interactions can be detected with lower classification metrics. The novelty of the proposed approach consists on the empirical modification of the IG algorithm, using tuning thresholds, to the specific problem of detecting user-object interactions in a context-aware shelf scenario.

## V. wIG IMPLEMENTATION AND EVALUATION

### A. Weighted Information Gain Metrics

The wIG user-object interaction measurement algorithm relies on its configuration parameters to enable a fine-grained classification. Specifically, two thresholds can be set up to control the granularity of the classification:

- **Maximum Information Gain threshold (0-0.5):** The maximum IG threshold defines the classification quality, since samples with lower IG (that is, less entropy) from the threshold would be discarded.
- **Features threshold (0-1):** It establishes the minimum amount of features to consider a valid interaction measurement.

By tuning these two thresholds, the system can be better adapted to each specific working scenario. These threshold are user configurable, or self-calibrated by the system when the metrics measurements decrease. Since the thresholds' values affect the performance of the system, it provides the possibility of deciding between a more restrictive configuration (higher thresholds) or a more permissible one. On one hand, a restrictive configuration will provide a lower percentage of well classified samples, increasing the accurateness but decreasing the sensibility (recall). On the other hand, a permissible configuration will consider samples with low entropy, thus, decreasing the classification accuracy.

The wIG classifier can be implemented in a variety of scenarios. We integrated wIG into an RFID-enabled context-aware shelf tracking labeled books, using off-the-shelf RFID devices, with the goal to track users interacting with the books. In this section, we describe our implementation based on the RFID-enabled context-aware shelf, we give details on empirical experiments with users, and evaluate wIG classification metrics and thresholds.

### B. Context-aware Shelf Prototype using wIG method

We implemented wIG on an RFID-enabled context-aware shelf, to empirically evaluate our user-object interaction detection system. Figure 2 depicts a general overview diagram of the system. An external display connected to the information system back-end can then be used to provide feedback to

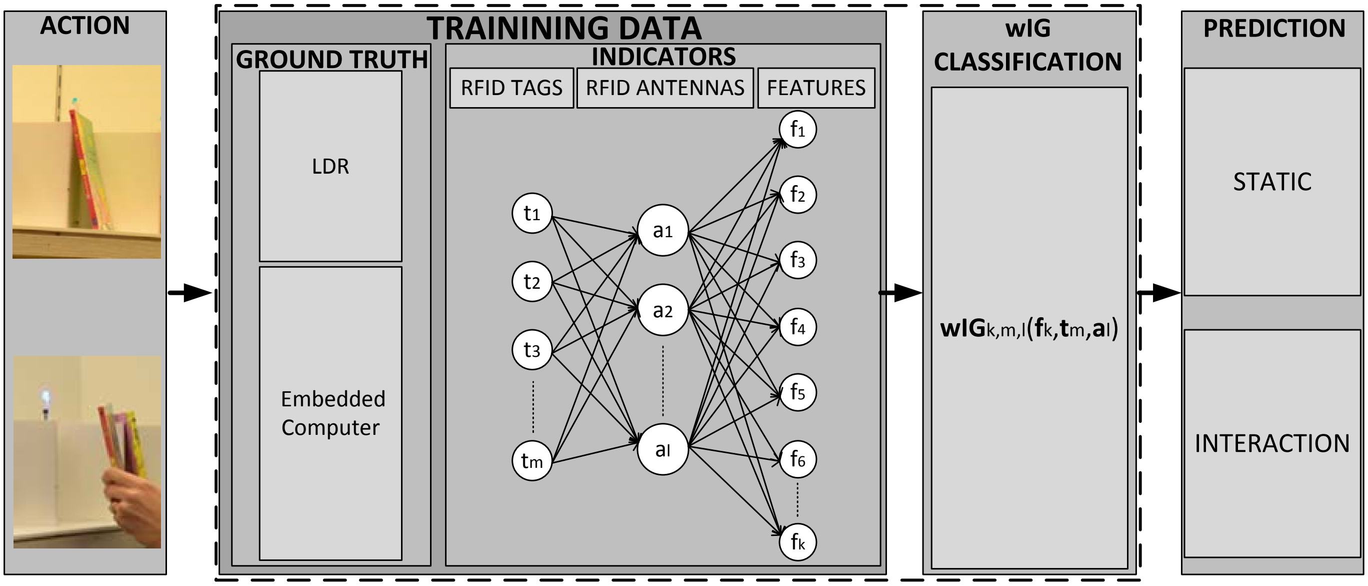


Fig. 2. Elements participating in the user-object interaction detection system.

the user (i.e. additional information on the interacted object). The context-aware shelf uses commercial off-the-shelf RFID equipment.

Figure 3 shows a user evaluating our proposed user-object interaction system. The user-object interaction devices are placed within a regular shelf. The system is composed of four RFID antennas behind the prototype, a number of books with an RFID label attach on the back of them. Each RFID antenna polls for RFID tags each approximately 250 ms (200 ms of read time + 50 ms of processing) obtaining four samples per second. An LDR placed between the structure and the book (red-straight arrow on Figure 3) provides the ground truth where an Arduino board collects the given signal. Data from both RFID and Arduino system are generated separately, and processed afterwards by a computer to generate a single dataset. The dataset evaluated in this section has been generated by the samples collected from an experiment of 20 minutes length carried out in a laboratory by volunteer users, who were we asked to interact with the tagged-books freely. The dataset result is composed by 1/3 of interacted samples by 2/3 of samples with no interaction as occur in real store.

We evaluate our proposal by using standard metrics Precision, Recall, F-Score and Accuracy. In terms of user-object interaction, those can be defined as:

- **Precision:** Measures the percentage of samples correctly classified by the wIG classifier between all samples classified as interaction by the ground truth.
- **Recall:** Measures the percentage of samples correctly classified by the wIG classifier between those samples which were or not well classified but the LDR sensor detected as interaction. This measure indicates the reliability of the user-object interaction system by avoiding false positive alarms.

Fig. 3. Example of object being interacted by a user, and other static objects on the shelf.

- **F-Score:** Measures the harmonic mean from Precision and Recall. It provides information about the correctness from both metrics.
- **Accuracy:** Measures the percentage of samples classified correctly out of all samples.

### C. Threshold Evaluation

Figure 4 shows four plots corresponding to each of the four metrics measurements Precision, Recall, F-Score and Accuracy. The y-axis represents the maximum IG threshold, and the x-axis define the percentage of features fitting the wIG threshold. The values of maximum IG threshold varies from 0 and 0.5 while the features threshold varies from 0 and 1. The darker the gray color the better the measure. The optimal point occurs with a maximum IG threshold of 0.34 and a feature threshold of 0.4. Notice that the higher the thresholds are, more restrictive the system is. Nevertheless, higher thresholds allow a better classification.

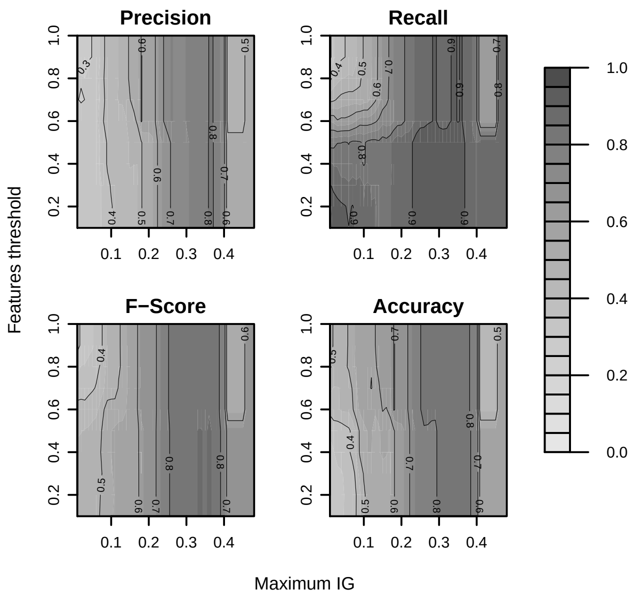


Fig. 4. Classification metrics. Optimal thresholds

The empirical results shown in this work depend on the features utilization (cf. Table I). In the experiments described in this work the features achieving better IGs, that is, better classifying user-object interactions, are *RSSI*, *RSSI MEAN*, *RSSI DIFF*, *RSSI STD*, *PHASE DIFF*, *PHASE MEAN* and *PHASE*. A deeper analysis on features is out of the scope of this paper, and is considered for future work.

### *D. wIG Algorithm Evaluation*

In this section we compare the wIG algorithm with the basic IG used in [16], and a Baseline algorithm based on absence/presence of the objects. We compared the evaluation of the four metrics measurements explained above: Precision, Recall, F-Score and Accuracy. We have used the same dataset as detailed in section V-B composed by 4000 samples.

TABLE II
SUMMARY OF THE PARAMETERS USED IN THE EXPERIMENTAL SETUP.

| Parameter | Value |
|---|---|
| RFID Standard | EPC Gen2 [2] & ISO 18,000 6C [20] |
| Max tag read throughput | 400 tags/s |
| Tx Power | 31.5 dBm |
| Sensitivity | -80 dBm |
| Q value | Dynamic |
| Read time | 200 ms + 50 ms processing |
| Antenna Beamwidth | ∼100 degree |
| Antenna Gain | 3.2 dBi |
| Passive RFID Tag IC | NXP U-Code G2iL |
| Sensors | 4 LDRs |
| Embedded computer | Arduino board |

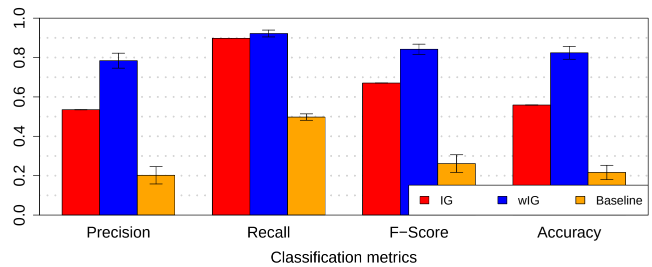


Fig. 5. Comparison of the classification metrics between the original IG, wIG, and a Baseline . The wIG algorithm achieves better results than the other techniques.

Figure 5 shows the evaluation results. We can observe how the wIG algorithm performs better than the other techniques in all the described metric measurements. The wIG algorithm Precision is higher (78.5%) than IG (53.5%) and Baseline (20.2%). The reliability of the system (Recall) is similar in the case of wIG (92.2%) and IG (89.8%), with both achieving excellent performance. The F-Score represents the weighted harmonic mean from Precision and Recall measurements, thus, the wIG algorithm achieves better metrics with an 84.2% while IG and Baseline obtain 67.1% and 26.2% respectively. Finally, the wIG algorithm obtains an Accuracy of (82.4%), over 20% compared with the other algorithms tested.

In conclusion, the wIG's better precision (detecting actual user-object interactions) improves the overall metrics compared with the basic IG algorithm, and Baseline methods. Furthermore, our classification approach performs over other standard state-of-the-art machine learning classifiers as described in Parada et al. [19].

## VI. CONCLUSION & FUTURE WORK

Online commerce is a step ahead in tailoring the user interests and needs thanks to the easiness of web browsing tracking. Obtaining similar information in brick-and-mortar stores is a hard and expensive task if performed manually or using vision-related techniques.

We propose the utilization of RFID-enabled context-aware shelf to provide additional information on users' interest in physical spaces. The wIG interaction detection system is an empirical, low-cost, and scalable user-object interaction classifier relying on the well known EPC Gen2 RFID standard. The classifier is autonomously trained to calibrate and improve classification. We have empirically evaluated our proposal with commercial off-the-shelf RFID equipment, achieving performance over 80%, improving state-of-the-art methods.

We envision a real store where users' interests and preferences are used in a privacy-preserving manner for the benefit of both users and retailers, as online commerce services do. The wIG algorithm could be used, together with RFID-enabled shelves, to collect user interests, feed real-time user-centric recommendation systems, independent context-aware shelf navigation for visually impaired users, and many other applications.

We plan to extend and improve the wIG interaction detection system. Our future work includes, but is not limited to:

- Extend the number of antennas and tagged-objects for large-scale experimentation
- Experiment with different objects to evaluate the effect of size, shape, material, etc.
- Use channel information to improve features based on PHASE
- Evaluation and improvement of features' contribution.
- Implement a real time visualization providing products' information, recommendations, etc.

## VII. Acknowledgment

A preliminary version of this paper was presented in the poster session of the IEEE RFID 2015 Conference [21]. We thank the positive comments and feedback received, which allowed us to improve this paper.

The authors acknowledge financial support from the Spanish Government through the projects TIN2011-27076-C03-02 CO-PRIVACY, and TIN2014-57364-C2-2-R SMARTGLACIS, and the Universitat Pompeu Fabra ICT PhD program through a travel grant.

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