Towards Measuring User-Object Interaction in IoT Spaces

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***Abstract*—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. We present the weighted Information Gain classifier (wIG), an empirical machine learning technique designed to reliably detect user-object interactions in a IoT context-aware shelf scenario, with the goal to measure user activity. Our proposal relies on UHF RFID features analysis, and sensors providing real-time ground truth feedback. We compare two versions of the wIG algorithm achieving up to 84% F-Score in classification. Our scalable and low-cost solution fully relies on state-of-the-art commercial equipment.**

I. INTRODUCTION

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. Most retailers already attach UHF RFID tags to their products, to monitor stock or speed up cash processes[3]. 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. Sellers could benefit from the information about all the user-object interactions taking place within the store if presented in a comprehensive manner for them. Our goal is, in the overall, to improve user's shopping experience by reliably measuring in real time user-object interaction in an unassisted manner, uniquely by means of RFID information.

II. PROBLEM MOTIVATION & RELATED WORK

Nowadays, customer satisfaction data are among the most frequently used indicators of market perceptions. 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.

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). Our approach to analyze user-object interaction is based on RFID measurements and the ground truth provided by sensors, allowing data extraction automation in a real implementation. Besides the actual high-level inventory information, we use ten features statistically based on RFID indicators such as received signal strength indicator (RSSI) and RF Phase (PHASE) to improve resolution on the user-object interaction. Our approach follows a similar approach as [4], selecting relevant indicators from which to extract meaningful activity information. However, instead of single feature utilization, we select multiple features for classification [5].

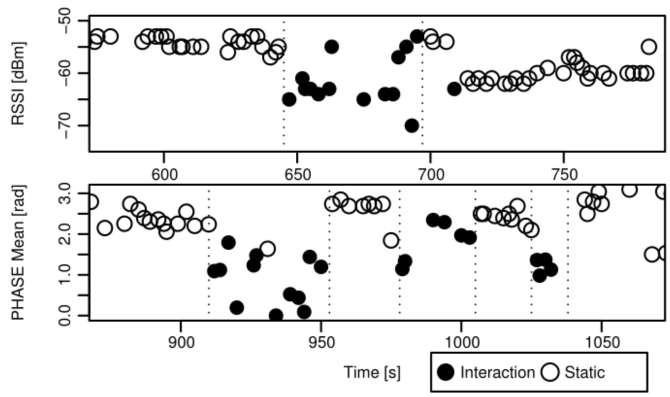

Fig. 1. RFID indicators like RSSI and Phase may describe object movement, which can be inferred as interaction with persons. Interaction and static samples in this figure are automatically determined by an LDR sensor.

III. IOT-BASED INTERACTION DETECTION PRINCIPLE

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 [6] for more details on UHF RFID PHASE extraction). Opposite, a static tag returns stable low-level measurements.

We propose to collect ground truth from a subset of tags using LDRs behind the labeled objects. A threshold, then, determines the object's state. Despite the reliability of this ground truth method, only a binary presence/absence state is obtained. However, the RFID descriptors return a richer information set on the labeled objects activity since they can be tracked even on users' hands. 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.

We present the weighted Information Gain classifier (wIG), an empirical supervised machine learning technique designed to fit the problem of detecting interactions in an RFID-enabled context-aware shelf scenario. Our proposal is based on the information gain (IG) algorithm [7] also known as the

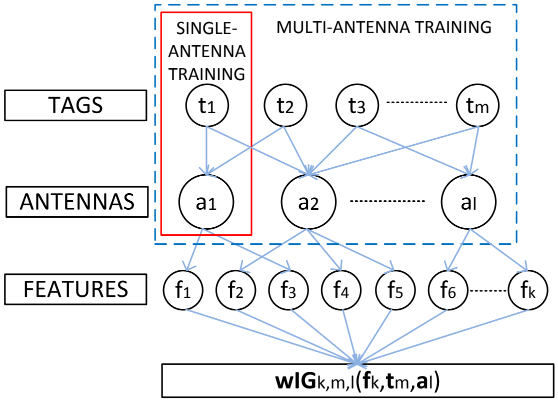

Fig. 2. Scheme of wIG system trained by a single-antenna, or multiple antennas.

Kullback-Leibler divergence. It can be interpreted as a measure of how well two event labels can be classified based on a given threshold. The higher the IG for a specific threshold, the more accurate the classification is. It is based on a preliminary empirical method described in [5], where the IG algorithm is applied to only three RFID features.

We compare two versions of the wIG algorithm. On the one hand, *single-antenna wIG* trains the classifier from one single labeled object (t_1), or a subset of labeled objects located in a reduced area, applying the trained classification to the rest of objects. On the other hand, *multi-antenna wIG* considers a larger set of ground truth sensors and tags ($t_1 \dots t_m$) for training. That is, in a context-aware shelf scenario, more than one antenna ($a_1 \dots a_l$) would be used for training. Thanks to the multiple ground truth input, multi-antenna wIG independently classifies from each set of tag-antenna (t_m-a_l), defining a single feature-antenna-tag IG value. This allows to consider only those samples with a good IG-defined threshold.

IV. wIG Initial Results

Figure 3 shows the context-aware shelf implemented in the laboratory, reproducing a real scenario. Volunteers were requested to take books off the shelf (one or more) from its static position temporally, and optionally return them to the shelf. In our case, interaction includes the amount of time the user holds the books on her hands. Once the book is removed, a light intensity difference is sampled at the LDR and the ground truth status switches from static to interacted. The experiment was composed by five books with an RFID EPC Gen2 tag stack on them. These books were held in a structure within the smart shelf equipped with four RFID antennas on the back. An LDR element was placed between each book and the structure in order to detect interactions, connected to an Arduino microcomputer sampling the LDRs to obtain the ground truth. The RFID system takes about one second to sample the whole shelf. Both RFID and sensors information were combined through timestamps in a computer to feed the supervised learning classificator.

Figure 4 summarizes classification metrics early results for both wIG modes, where the single-antenna training mode achieves an F-Score of about 71% while multi-antenna achieves 84% F-Score. Notice that *Recall* metrics achieve the best results, meaning that the system will avoid most false

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

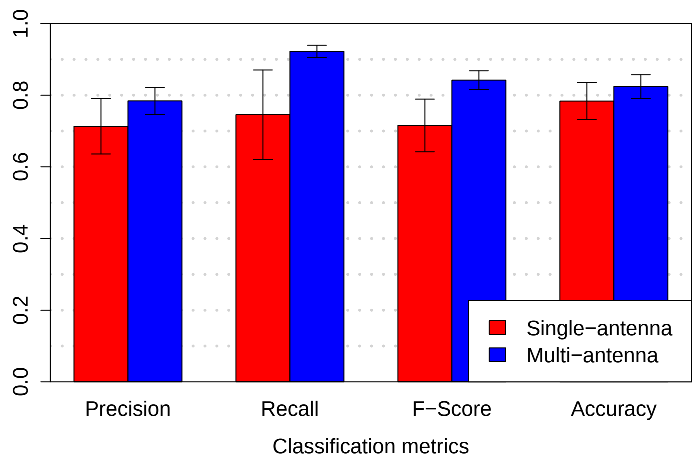

Fig. 4. Multi-antenna finer-grained method achieves better classification metrics, with emphasis on avoiding false negative samples (Recall).

positives. As ongoing work, we are extending experimentation, and improving the wIG interaction detection system by extending the number of antennas and tagged-objects for large-scale tests.

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