Statistical Features for Objects Localization with Passive RFID in Smart Homes

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Abstract. Smart homes offer considerable potential to facilitate aging at home and, therefore, to reduce healthcare costs, both in financial and human resources. To implement the smart home dream, an artificial intelligence has to be able to identify, in real-time, the ongoing activity of daily living with a fine-grained granularity. Despite the recent and ongoing improvements, the limitation of the literature on this subject primarily concerns the quality of the information which can be inferred from standard ubiquitous sensors in a smart home. Passive Radio-Frequency Identification is one of the technology that can help improving activity recognition through the tracking of the objects used by the resident in real-time. This paper builds upon the literature on objects tracking to propose a machine learning scheme exploiting statistical features to transform the signal strength into useful qualitative spatial information. The method has an overall accuracy of 95.98%, which is an improvement of 8.26% over previous work.

Keywords: Smart environment · Passive RFID · Indoor localization
Machine learning · Data mining

1 Introduction

World population aging is a situation which most government are now fully aware of the potential consequences, and, therefore, are establishing new policies accordingly to this societal change [1]. While it has been predicted a while ago, the consequence of this continuous aging will be felt for the next few decades to come. One challenge that may be linked directly to this reality is the increasing difficulty to sustain adequate healthcare services to the population. Furthermore, while the population is aging, the life expectancy has also been increasing steadily. Therefore, the active population able to pay for public healthcare is shrinking percentage wise. This problem is quite complex, and researchers, not for profit organizations, and governments now seem to agree that the solutions will be found through innovation from all disciplines involved in the healthcare chain [2].

The miniaturization of technology and the evolution of artificial intelligence (through algorithms improvement and better computer power) enables the researchers to contemplate the implementation of the old smart home dream to alleviate the weight on the fragile healthcare system. Indeed, a large proportion of the direct or indirect healthcare costs can be attributed to the autonomy loss of elders which often result in either a complete care of the person by health professionals (in a long term care establishment or senior housing for non-autonomous) or in a higher frequency of

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hospital admission. Many researchers from multiple disciplines, including the members of our laboratory, believe that one of the most important contribution that could be made to relieve the healthcare system would be to enable aging at home through the implementation of smart homes [3]. In this context, a smart home is a technologically enhanced house or residence able to ensure the security of its resident, monitor his health status, and assist him in his activities of daily living (ADLs) in real-time [4]. To do so, smart homes are generally equipped with ubiquitous sensors (passive infrared, electromagnetic contact, etc.), wearable sensors and/or video camera [4–6].

One of the major challenges of implementing a smart home based solution for aging in place is to be able to recognize, in real-time, the ongoing ADLs of the resident [7]. Several methods have been proposed over the past decade, but this endeavor remain problematic due to the low granularity of the current solutions. The granularity, in activity recognition, refers to the level of abstraction provided by the method. For instance, from the lowest to the highest granularity, the same ongoing ADL could be defined as: *Cooking*, *Preparing pasta*, *Preparing shrimp fettucine Alfredo*, or even as the atomic step *Putting fettucine in the boiling water*. While our team at the LIARA laboratory is fairly sensors agnostic [8, 9], we believe that one of the solutions with the highest potential to solve this granularity problem is the passive Radio-Frequency Identification (RFID) technology. The main advantage of passive RFID is that several tags can be installed on daily usage objects in the smart home to enable their tracking in real-time [9]. Therefore, such system could provide highly reliable spatial information to feed an activity recognition algorithm for better granularity.

In this paper, a localization system based on techniques for machine learning/data mining is proposed. The method build upon the work of Bergeron *et al.* [10] which is, in our knowledge, the only example of localization of several objects based on supervised data mining. Indeed, very few authors have worked on the problem of localizing daily usage object, and unfortunately, the best methods for humans/robots tracking often cannot be used straightforwardly [11, 12] because the technology used is too big (require batteries, antennas on the objects, etc.), is too costly, or requires several references points (disposing those in a smart home is not always feasible). As it will be argued further in the paper, daily objects localization is more challenging than human or robot tracking, and the accuracy and precision of the state-of-the-art is still arbitrary. To address this challenge, in this paper, the RFID Received Signal Strength Indication (RSSI) is viewed as a time-series. The research question that was formulated in this project is:"How useful at improving RFID localization methods would be the statistical features commonly used in machine learning?".

The datasets used in this paper were all generated from real data collected in full-scale smart home infrastructures and are available to the scientific community at www.Kevin-Bouchard.com.

2 Related Work

Localization is an old topic of research [13]. Over the years, a plethora of technologies and techniques have been developed and tested for several purposes. This paper could not begin to cover such a vast topic and therefore we encourage the reader to see [14] for a more complete review of the existing works. For wireless technology, there are three widely used techniques. The first one, is the proximity based technique [15]. This technique refer to the association of the tracked object to the closest known point of reference, usually an antenna. The idea is straightforward. The strongest signal among the references determines the position. The reference tags introduced by the LANDMARC system is often categorized as a proximity based technique [16]. The idea is to install tags at known location to use them for accurate tracking of moving tags. The second family are the lateration techniques which use geometric properties to localize an entity. Trilateration is the most often used lateration technique for radio-frequency technologies. The idea is to map the RSSI to a distance measure from the antennas and draw virtual ellipsoid to pinpoint the location at the intersection of few reference points [9]. Finally, the last family of techniques is the learning based methods such as the very popular fingerprinting technique [17]. The fingerprinting technique is usually used in conjunction with a better, more precise, localization system to build a radio map of the environment. The technique is, then, to use the learned map and compare, in real-time, the RSSI to associate the tracked entity to the closest location in a similar fashion than with landmarks. More classical machine learning techniques are less popular [10], since the performance of fingerprinting is usually better. The main drawback is, however, the requirement for the high performance localization system (usually based on ultrasonic sensors) [18].

3 Methodology

In this section, the goal is to explain the methodology that was used to validate the research question formulated in the introduction. While the emphasis of this paper is on the localization of one object in one smart home, the reader should keep in mind the bigger picture, which is about tracking several objects in real-time for ADLs recognition in smart homes for aging at home. Our team has already used the spatial data from passive RFID localization in activity recognition system in the past [19] and improvements in the localization tend translate directly in better activity recognition.

This paper is based on the work of Bergeron *et al.* [10] which was conducted with the LIARA and the DOMUS teams from which the author is a member. The method that was exploited in the aforementioned paper relied, similarly to the literature, on using the raw RSSI signal from the passive tags to perform the localization. In contrast, this project see the RSSI as a time-series. Therefore, despite the low sampling, the localization is performed over a data window, which is an aggregation of many readings. The importance of this work relies on the premise that daily objects localization is more difficult than human/robot localization. The arguments are that daily objects can be very small (e.g.: a spoon, or a fork), numerous (in the kitchen there are several plates, containers, glasses, etc.) and that occlusion will often occur.

3.1 Smart Home

The datasets used in this project were collected in a realistic smart home setting [10]. The smart home is a full scale apartment including a bedroom, a kitchen, a dining room, a living room and a bathroom. It is equipped with 20 polarized directional antennas distributed to cover the entire surface. These antennas are connected to five RFID readers and work on the 928 MHz band as specified by the Canadian Radio-Television and Telecommunications Commision (CRTC). Therefore, they have to be strategically installed to minimize collisions and maximize coverage. Collisions cannot occur among the antennas connected to the same reader since they work on round robin. A derogation can often be obtained through the CRTC to change the band, but since our goal is to use the smart homes for aging in place, this would not be practical. In theory, the RFID system can collect the tags ID up to every 20 ms. However, this is not a real-time system, thus the results are often very different. In practice, it has been observed to be reliably able to collect data under 100 ms (Fig. 1).

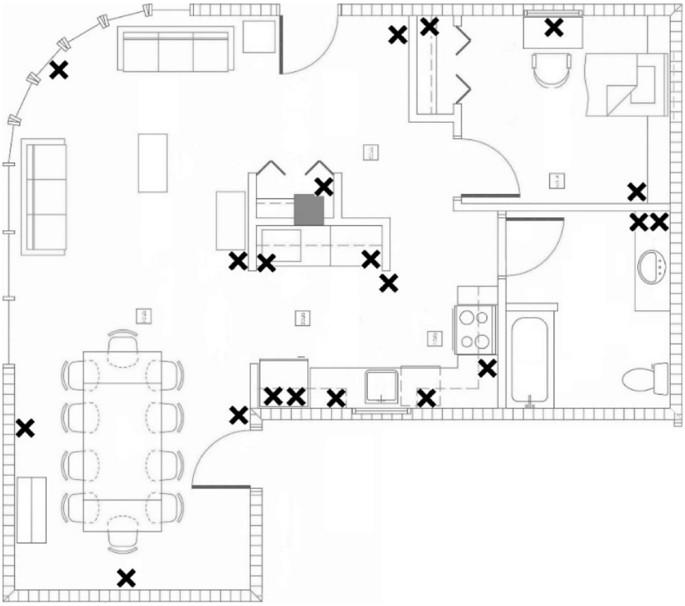

Fig. 1. Aerial view of the smart home and the placement of the antennas from [10].

3.2 Design of Qualitative Zones

In our research context, qualitative information refers to abstracting quantitative information (precise quantities, often continuous variables) into a discrete number of classes or values (e.g.: from GPS coordinates to spatial regions/zones). As I argued in [19], qualitative spatial information is more useful for activity recognition than quantitative. There are two main arguments to this claim. First, it is easier to define (or learn) reasoning rules on qualitative information due to a smaller number of possibilities and better defined classes (weaker interdependencies). Second, qualitative information is an abstraction layer over the quantitative information and therefore it can hide the inherent lack of accuracy. It is especially true in the case of RFID localization.

Precise quantitative methods such as trilateration will always results in different coordinates from iteration to iteration [9], while an abstraction layer of qualitative zones can result into a relatively stable position (albeit being less precise).

To create the qualitative zones, each room is associated with a virtual grid (composed of squares). In the original paper, the qualitative zones were defined heterogeneously. Each room had its own zone's size. The team also made available datasets for alternative zone size in the kitchen and the living room (the datasets are also available at www.Kevin-Bouchard.com). The size of the zones is determined with (1) how much precision is needed in the activity recognition and (2) how many antennas cover the room. They are also limited by the inherent precision of RFID systems. The kitchen and the dining room have respectively 238 and 324 zones of 20 cm by 20 cm. The bathroom and the bedroom have zones of 60 cm by 60 cm and the other rooms have zones of 75 cm by 75 cm.

3.3 Datasets

To understand the properties of the datasets that were used in this project, it is mandatory to first discuss the original datasets published in [10]. The learning was done independently on each of the room. The classes are the set of qualitative zones. There are a total of 673 zones/classes. To collect the data for learning, an object (a plastic bottle of water) equipped with four tags was used. The merging was done through tag selection (the strongest tag was always selected). To understand the impact of using more objects with various shape in real-time, the reader should consult [20]. In the original datasets, fifty readings per classes for each antennas were recorded resulting in 33 650 vectors of twenty RSSI +1 class or 673 000 data. The variation of the RSSI values is bounded between −38 to −69. As a consequence, the datasets have a high number of classes in proportion to the number of possible values.

In this project, the raw RSSI is transformed to obtain one time-series per RFID antenna. Therefore, the transformed datasets are composed of vectors of features computed over the windows of raw RSSI. The features used in the project are discussed in Sect. 3.4. Since the original datasets have a relatively low number of samples per class, the window size is tricky to select. Moreover, for real-time localization of objects, the window must be small enough to avoid lagging in the positioning. Since the system can reliably collect data from 100 ms and more, it seems appropriate to limit the window to between 5 to 10 readings. See the Sect. 4.2 for a better understanding of the impact of selecting a different window size. Finally, in machine learning, there is often the question of sliding windows or not. In our case, the number of samples is actually too low to not use sliding windows for learning. The window slide for each new vector.

3.4 Statistical Features

To exploit the time-series extracted, features were computed over the sliding windows. A wide range of features were added, although the choice was limited by the properties of the datasets. For example, the widely used kurtosis and skewness could not be used because they are extremely affected by sampling [21]. Of course, all statistical features are affected to some extend by the low sampling, but since it could not be predicted how this would translate into the learned models (the sampling could have the effect of making the features highly discriminative), only the statistical features less likely to be impacted were selected. Considering M is the matrix of the data window made of k lines and n columns (the features), the Table 1 describe the features used. There are nine statistical features applied to each time-series and eight applied globally (to all 20 time-series). For instance, the *Mean RSSI* is the sum of all RSSI in a window for an antenna divided by the window size. The *Global Mean RSSI* is the sum of all RSSI in that window divided by the total number of elements in that window ($n * k$). Consequently, the size of each features vector is 189 (20 time-series * 9 statistical features + 8 global features + 1 class = 189).

Table 1. The list of features applied on the time-series.

Mean RSSI	Global mean RSSI	Min RSSI
$\bar{x}_j = \frac{\sum_{i=1}^{k} x_{i,j}}{k}$	$GAvg = \frac{\sum_{i=1}^{k}\sum_{j=1}^{n} x_{i,j}}{n * k}$	$\min(j) = \min_k\{x_{k,j}\}$
Variance of RSSI	Standard deviation of RSSI	Global min RSSI
$Var(X_j) = \frac{1}{k}\sum_{i=1}^{k}(x_{i,j} - \bar{x}_j)^2$	$\sigma_j = \sqrt{Var(X_j)}$	$GMin = \min_n\{\min(j)\}$
Count non-zero	Global mean standard dev.	Max RSSI
$NZ_j = \sum_{i=1}^{k} 1_{\mathbb{R}_{!=0}}(x_{i,j})$	$GStDev = \frac{1}{n}\sum_{j=1}^{n}\sigma_j$	$\max(j) = \max_k\{x_{k,j}\}$
Global NZ	Absolute energy	Global max RSSI
$GNZ = \sum_{j=1}^{n} NZ_j$	$E_j = \sum_{i=1}^{k} x_{i,j}^2$	$GMax = \max_n\{\max(j)\}$
Absolute sum of changes	Global absolute energy	Mean RSSI change
$SC_j = \sum_{i=1}^{k} \lvert x_{i,j} - x_{i-1,j}\rvert$	$GE = \sum_{j=1}^{n} E_j$	$\frac{1}{k}\sum_{i=1}^{k} x_{i,j} - x_{i-1,j}$
Global SC	Global total power	
$GSC = \sum_{j=1}^{n} SC_j$	$Tp = \sum_{i=1}^{k}\sum_{j=1}^{n} x_{i,j}$	

Most of these features are common knowledge, but few of them may need a proper introduction. The *Count Non-Zero*, and by extend the *Global NZ*, count the number of occurrences where the signal was read, or to simply put where the RSSI was different than zero. The *Absolute Energy* is the sum over the squared RSSI values. The *Mean RSSI Change* is the average fluctuation in RSSI that can be expected on the time-series. The *Absolute Sum of Changes* (and *Global SC*) is the sum over the absolute difference between each consecutive RSSI values. Finally, the *Global Total Power* is the sum of all RSSI values over each time-series of the window.

4 Experiments and Results

The first set of experiments that were done had the goal of comparing the results of the features based localization with the original experiments presented in [10]. In the paper, Weka [22], a well-known package of tools and algorithms for data mining, was exploited to learn the models for localization. The default parameters were selected to simplify reproduction of the results and a standard 10-fold cross validation was used to calculate the accuracy. The same experiment was reproduced. The accuracy and performance difference of the algorithm for each of the new datasets (with window size = 5) is compiled in Table 2. The reader should take note that for space purpose only the most interesting algorithms are presented, but in all but one case the accuracy improved over the original method. For K-NN, k = 1 was selected according to the results of testing for k = 1 to 5 in [10]. As the reader can see, in most cases the improvement was significant, especially for algorithm with a lower performance in [10]. Moreover, we can observe that for room with smaller zones and a higher number of classes the improvement was most of the time between 10 to 25%. Overall, the weighted average of the F-measures is 96.097% and the Kappa is 96.062%. The standard deviation of both the F-measures and the Kappa are 5.78% with the lowest score of respectively 0.685 and 0.683.

Table 2. Accuracy for the learning algorithms on each dataset and the performance divergence from [10].

Dataset		Hall	Living Room	Kitchen	Dining Room	Bedroom	Bathroom	Average
Change in % - Accuracy	CART	99.6%	98.1%	94.0%	95.6%	99.0%	98.4%	**97.4%**
		4.0%	5.7%	20.6%	23.1%	7.5%	8.1%	**11.5%**
	J48 (C4.5)	99.0%	98.8%	96.4%	96.4%	99.1%	98.9%	**98.1%**
		2.2%	6.8%	21.4%	23.1%	6.2%	7.2%	**11.1%**
	1-NN	93.5%	98.2%	68.5%	91.4%	98.8%	95.2%	**90.9%**
		-1.4%	3.4%	-10.3%	18.2%	5.6%	4.8%	**3.4%**
	NaiveBaye	98.9%	99.0%	89.6%	94.9%	99.6%	99.7%	**97.0%**
		2.5%	1.3%	4.6%	20.0%	3.9%	4.6%	**6.2%**
	Random Tree	97.7%	96.0%	89.6%	87.1%	95.8%	95.3%	**93.6%**
		2.1%	6.6%	21.8%	16.0%	6.0%	7.2%	**9.9%**
	Random Forest	99.9%	100.0%	99.8%	98.8%	100.0%	99.8%	**99.7%**
		2.1%	2.4%	10.9%	22.1%	3.5%	3.7%	**7.4%**

4.1 The Impacts of Features

The impact of the features based datasets is more than the accuracy of the learning algorithms. One thing that might be relevant is the complexity of the models built from the new datasets compared to the standard datasets. The tree algorithms such as CART or J48 are useful to do this type of analysis. Random Tree has a random factor that could distort the result, and its complement, Random Forest, is harder to analyze since it is constructed (in our case) of a hundred random trees. When looking at the tree generated by CART and the tree generated by J48 for the *dining room* dataset (324 classes), the size are respectively 1169 and 1187 for the models build with the features. With the raw RSSI of the *dining room*, the tree size is more than the double (CART: 2671 & J48: 2559). This suggest that the new models are more general due to the higher information quality resulting from the features. For simpler room such as the *hall* (X classes), the difference is less staggering. The models size are 47 & 57 for the raw RSSI and 31 & 33 for the features datasets. Notwithstanding its lesser importance, the time to build the models was also compared. Surprisingly, in most cases the time difference between the raw RSSI datasets and the features datasets was not significant. Moreover, it actually improves with Random Tree and (obviously) Random Forest. Finally, the features enable the merging of all the room's datasets together for a unified learning. Although the results are slightly lower, the accuracy is still very high. For example, with J48, the accuracy, Kappa and F-measure are 96.91%. From the 673 different classes, a tree of size 2397 is constructed. With 1-NN, the accuracy drop a little bit more to 82.31%, but for CART it also improves to 95.45% albeit increasing the learning time to 472 s.

4.2 The Impacts of Windowing

The last topic that needs to be discussed is the impact of the window size. Combined datasets were generated for window size 10, 15 and 20 to evaluate how it would affect the accuracy. For J48, the accuracy goes from 96.9% for window size 5 to respectively 99.06%, 99.53% and 99.53%. Obviously, since the accuracy is being already very high, the upside of bigger windows is limited. K-NN is a better candidate to observe this. With window size 5, K-NN accuracy is 82.31%. With the bigger windows, it climb to respectively 93.37%, 97.29% and 98.42%. These observations seem to suggest, as it was expected, that some features become more useful when sampling is more important. However, to use in a real-time localization system, these windows will increase the apparent lag in the positions of the objects. Moreover, with some algorithms such as Random Forest, the accuracy is already very high which hamper the usefulness of increasing the window size. While the learning time of Random Forest is considerable, the resulting model is easily usable in real-time.

5 Conclusion

In this paper, passive RFID was used to localize objects in a smart home for aging in place. The goal was to validate if statistical features could be used to build upon the existing work exploiting machine learning to create automatically localization models.

The experiments demonstrated a gain of 8.26% on average over [10]. In the future, the learned models will be put to test within an activity recognition system at the LIARA smart home in order to confirm that the localization performance gain translate into better recognition of ADLs. In conclusion, we encourage the readers to download the datasets created for this project and use them to pursue their own researches.

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