Simple Objects Tracking System for Smart Homes

A Passive RFID Approach Based on Decision Trees

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***Abstract*—One of the greatest challenge of research on smart homes is to be able to recognize the ongoing Activity of Daily Living (ADL) in real-time and make prediction on the future action of the resident. To accomplish this task, it is important to have accurate information. In this paper, we present a novel passive RFID Indoor Tracking System (ITS). The goal of this ITS was to create a simple solution from data mining that could be easily deployed in any smart environment without requiring specialized human expertise on RFID. The tracking average 80% of accuracy and show promising results for large scale deployment.**

Keywords— Smart home; Tracking; RFID; Decision Trees;

I. Introduction

Assistive technologies have gained traction in the ambient intelligence research community over the past few years [1]. Some believe that they could be exploited to counter the effect of the world population aging [2]. For example, it is predicted that health care costs will continue to grow at a faster rate than the economy for the next decades [3]. Toward that goal, many research laboratories around the world are working on assistive smart home [4, 5] to enable aging in place and thus limiting the need of costly human resources. A smart home is a living place enhanced with a wide range of sensors, actuators and effectors [6]. One of the main challenge is the fundamental recognition (and prediction) of the inhabitant ongoing Activity of Daily Living (ADL) [7]. The main limitation of the literature on activity recognition is the low granularity of the ADLs that can be recognized by the proposed methods. To palliate to this issue, it is required to obtain more information on the state of the environment in which the ADL is realized. To do so, some opt to define precise models of ADL in a large logical library [8], but it is a very difficult and time consuming task. It can also be addressed by exploiting video cameras that enable to capture much more information. However, vision sensors and wearable [9] are often considered as more invasive than ambient technologies [10].

Many researchers such as the team of the LIARA lab and the team of the DOMUS lab are turning toward the exploitation of passive RFID technology to acquire spatial information on the environment. To do so, daily life objects in the smart home can be equipped with tags in order to be located by antennas distributed into the environment. The problem of developing passive RFID Indoor Tracking System (ITS) is also well documented in the literature [11]. However, the existing methods are generally designed for robots tracking or industrial contexts which are not adapted to the tracking of objects inside a busy smart home. Additionally, most of them depends on mathematical models that must be precisely configured and tweaked. Mathematical models are exploited to enable high precision, but in our context, it is more important to have an accurate and a simple to implement system.

For the sake of repeatability and to contribute further to the research community, all datasets collected for the experiments presented in this paper are available online on Dr. Bouchard website: www.Kevin-Bouchard.com.

II. Related Work

In this section, we present the main families of approaches to passive RFID positioning and tracking. Most algorithms that can be found in the literature are based on the reference tags principle first exploited by the LANDMARC system [12]. The basic idea, is to exploit the Received Signal Strength Indication (RSSI) of nearby tags fixed at known positions to adjust the RSSI of the tracked tags. The method can be improved with various statistical filters [13]. LANDMARC based systems work very well in general, but they need to be exploited on a two-dimensional plane. The second family of algorithms is based on trilateration [14] and triangulation principles [15]. Trilateration uses RSSI and convert it to distance from antennas to draw imaginary circles. The position is the intersection point between three circles. Triangulation cannot be performed with all RFID systems. To do it, it requires to have the capability to calculate the angle of arrival. It is with the angles from three antennas that an intersection point can be found. Finally, the last family exploits data mining and other learning algorithms. However, work on this family are scarce and mostly regards other wireless technologies. For example, Yim et al. [16] exploited wireless local area network access point to build a decision tree during the off-line phase in order to determine the user's location.

III. Methodology

In this research, the goal was to design a new Indoor Tracking System (ITS) capable of tracking daily life objects in real time in a smart home from passive RFID tags. The ITS needed to be simple to implement yet generalizable to new smart home infrastructure. It was chosen to create a qualitative ITS which return a general logical zone instead of a precise position. This system was created with Decision Trees (DTs). There are many advantages to use DTs for tracking. First, the training process is very simple to reproduce. It is not necessary to be an expert to achieve it. Second, the method can be adapted to new RFID infrastructure easily by simply repeating the learning phase. Third, the tracking corresponds mostly to traveling a tree which is very fast. The rest of this section is as follow: we first give some details about our positioning system, then we present the object we tracked.

A. Indoor positioning system

To begin with our methodology, we first need to describe the most important part of an ITS, the positioning system. In a previous experiment, we built a qualitative indoor positioning system (IPS) using decision trees, more precisely a random forest. Back then, we tested several algorithms (C4.5, CAART, Neural Networks, etc.) and found that a random forest resulted in the best overall accuracy for a fast training which is a very important criterion in our context. Therefore, for the ITS, we use a random forest of 250 random trees built with the data from the first experiment. This IPS as an accuracy ranging from 80% to 95% depending on the room of our smart home. The qualitative tracking relies upon named zones of a certain dimension. These dimensions range from 20cm x 20cm in the kitchen and the dining room to 75cm x 75cm in the hall and the living room. Otherwise, it is 60cm x 60cm.

When we built the IPS, the antennas were set to emit at interval of 750ms and we recorded fifty readings per zone. The IPS uses twenty antennas disposed strategically to cover all of the apartment. Fig. 2, shows a map of the DOMUS apartment.

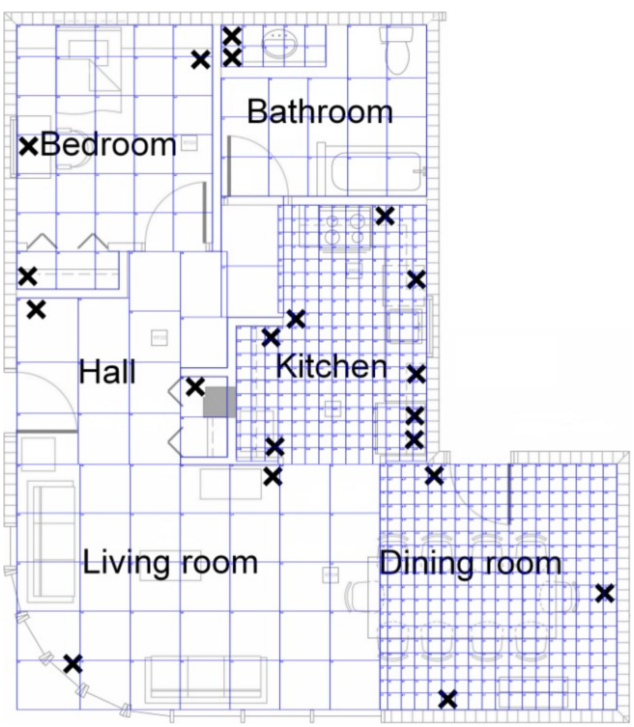

Fig.2. Map of the DOMUS' smart home. The RFID antennas are marked by a X. The grid represents the qualitative zones.

The map shows all the qualitative zones used by the IPS. The tracking algorithm also uses these zones. The movement of the tracked object is a directed sequence of zones. To each room is associated a different random forest trained with a different dataset. The IPS uses six different datasets containing fifty classified readings from each zone. We consider that the room where the activity is happening is known.

B. Tracked object

Once we have an accurate positioning system, we need an object to track. The same object used to create the IPS was exploited again. It is a reusable plastic bottle of water of about 600ml of capacity. Four class 3 passive RFID tags are installed on it, each one facing a different direction. This way, we ensure that there is always a tag directly facing an antenna, thus increasing the stability of the Received Signal Strength Indication (RSSI). Then the four resulting readings are programmatically merged into a single one containing the maximal value for each antenna. Therefore, a reading from the bottle consists in a vector of twenty integer representing the highest value collected by tags during a certain interval of time. When building the IPS, this certain interval was 750ms. However, this is way too slow for a real time tracking system. The interval was reduced to the minimal value achievable with our passive RFID system of 20ms.

C. Collecting a dataset

The next and final step of the physical part of our experiment was to gather data associated with paths to track. To do so, four plausible paths for each room were created (i.e.: trajectories that could be part of a normal activity of daily living). We tried to cover most of the daily living surface. Paths also have a varying length, matching the activity they tend to mimic. The paths were precisely drawn in the smart home with electrical tape. When taking measure, the participant was ordered to place the bottle over the tape and moves at slow speed following the tape. This process was repeated ten times for each path. In total, this first practical experiment gave us 240 paths we can evaluate accuracy on.

IV. EXPERIMENTATION AND RESULTS

An ADL recognition algorithm like the one we planned to design needs a real-time tracking system. In the previous section, we presented how we gathered the data required to build this system. In this section, we first present how we evaluated the accuracy of our tracking system, then we present the filters we used in order to increase the accuracy.

A. Accuracy evaluation

There are many ways to evaluate the accuracy of a tracking system. We chose to only compare the practical sequence of crossed zones versus the theoretical sequence, the path. There again, there were many possible metrics. Here are the four we selected.

1) Targeted Zones Found

This first metric (TZF) is purely statistical. Let **S** be the set containing the theoretical zones and **P** the set of the zones found by the tracking system. Then, the number of targeted zones is simply the cardinality of the intersection of those two bags. To compare sequence between them, we divide this number by the cardinality of **S**.

2) Sequential Targeted Zones Found

This second metric (STZF) looks like the first one, but with a temporal factor. It counts the number of practical zones that are found in the theoretical order. If the theoretical sequence says that **b1** comes after **a1**, then the measure will only count **b1** if the zone **a1** has already been seen. The measure does not require **a1** and **b1** to be directly one after the other, only that they are in the right order. Once again, we divide the number of zones correctly identified by the cardinality of **S** to compare sequences between them.

3) Levenshtein distance

The Levenshtein distance (L dist), also referred as the edit distance, is a well-known measure to compare sequences. We use it to find the difference between the practical sequence and the theoretical one. We use an insertion and deletion cost of one and a replacement cost of two. As you will see, this measure is not very useful with our data because the length difference between the practical and the theoretical sequences is too important.

4) Euclidiean distance

The last metric we used is the Euclidean distance (E dist). We need to perform a pre-treatment to make sure both sequences are of the same length. To do so, we take the raw data from the antennas for the whole path and we divide it in **|S|** bags. We then average each bag to get a single vector that we can ask our IPS to classify. We compute the Euclidean distance between this averaged zone and the reference zone and sum all the distances together to find the distance between the theoretical sequence and the practical readings. Finally, we divide the sum by **|S|** to get the average distance of the zones. Table I shows the results we obtained with those four metrics on the six rooms. As we can see, we do not even reach 50% of zone recognition in average, and not even 25% if we consider the sequence. The other metrics show that the distance between the sequences is reasonable. The Euclidean distance shows that we do not miss by really far for most room. In the kitchen, the system only miss by an average of 60cm, which is not critical in most cases when doing ADL recognition.

B. Filters

The accuracy we got with the raw data indicated us that there were a lot of room for improvement using post-treatment. While looking at a real-time map of the tracked object, we found out that the readings were not really stable, the object often teleporting really far of its true position. We developed two filters with the goal of stabilising the readings and the predicted zones.

1) Moving Average

The first filter we implemented is a trivial one, the simple moving average (SMA). The idea is to replace each new reading by the average of the reading of the N previous ones, were N is chosen with regards on the number of readings we get for each zone when moving or to simply put, the non null readings. The SMA help stabilising our data by significantly reducing the effect of noise. In a second time, we extended the moving average to its general case. It can be expressed as

TABLE I. RAW RESULTS

Metric	***TZF***	***STZF***	***L dist***	***E dist***
Bedroom	0,333	0,196	68,275	2,578
Bathroom	0,589	0,311	70	4,804
Hall	0,538	0,347	41,975	1,287
Kitchen	0,372	0,179	101,225	3,353
Living room	0,591	0,327	95,525	2,325
Dining room	0,114	0,057	71,175	7,101
Average	0,423	0,236	74,696	3,575

$$\mathrm{\bar{R}} = \sum_{n=0}^{N-1} \mathrm{C_n} * \mathrm{R_{N-n}} \Big/ \sum_{n=0}^{N-1} \mathrm{C_n} \tag{1}$$

Were $\bar{R}$ is the weighted average, R_{N-n} is the Nth reading and C_n is the Cth weight coefficient. Note that we consider N_0 as being the current reading. We also have to divide by the sum of all coefficients to make sure they sum to one. We tried four different distributions for the weighting. The first weighting function we implemented is the inverse natural logarithm function. Table II clearly shows that the accuracy increase with N, while still staying under the accuracy of the raw data and therefore, also under the accuracy of the simple moving average. The second distribution we used is a simple decreasing linear function. The idea is to decrease the importance of older readings in a linear way, as in

$$C_n = 1 - 0.1 * n \tag{2}$$

An interesting fact about this function is that the tenth value is nullified. Like the log function, the linear function increase accuracy as **n** grow bigger. This is the weight function that works best with our data, as is it the only one that achieve a gain of accuracy over the raw data. The next function we implemented is the inverse exponential function, with a base 2. Mathematically, it is

$$C_n = 1/2^{an} \tag{3}$$

In simple words, it means that every older reading weights half less than the preceding one when $a = 1$. We tried many value for the modifier a. With $a = 1$ the results are terrible. However, with $a = 1/8$ or $a = 1/16$ the results are much better. The last weighting distribution is the inverse factorial. The mathematical expression of our coefficient is

$$C_n = 1/an! \tag{4}$$

Where $n!$ is the factorial of n. Since the factorial rapidly increase, the length of the moving average (N) has no impact on the result. We therefore only use N=10 and tweak the modifier a instead. Of the four weighting distributions we tried, the linear one offer the best performance without tweaking. However, we were able to obtain higher result on all metrics by tweaking the factorial distribution. Both seems to outperform the SMA indicating that giving less weight to older readings is a good idea. We suppose that better results could be

TABLE II. EFFECT OF N AND THE WEIGHT FUNCTION WITH THE MOVING AVERAGE IN THE KITCHEN

		Metric			
N	**Weight function**	***TZF***	***STZF***	***L dist***	***E dist***
20	Log	0,240	0,104	119,325	6,309
30	Log	0,288	0,121	107,375	6,203
40	Log	0,291	0,120	101,150	6,300
20	Linear	0,256	0,142	165,175	6,375
30	Linear	0,408	0,185	141,675	6,262
40	Linear	0,457	0,206	108,250	5,955
10	Exp $a = 1/8$	0,191	0,092	122,825	6,193
20	Exp $a = 1/8$	0,232	0,105	119,375	6,405
10	Exp $a = 1/16$	0,245	0,112	128,225	6,211
20	Exp $a = 1/16$	0,321	0,145	114,65	6,453
10	Factorial $a = 1/4$	0,211	0,107	123,425	5,105
10	Factorial $a = 1/8$	0,364	0,166	132,95	4,178
10	Factorial $a = 1/32$	0,453	0,219	137,5	3,819
10	Factorial $a = 1/128$	0,487	0,246	136,625	3,865

obtained with a more sophisticated tuning of any of the distributions.

2) Limiting neightbor

The last filter we integrated to our ITS is a less restrictive version of the blocking neighbor. Instead of rejecting movement between zones that are not neighbor to each other, we limit the movement to only one zone at the time. Again, let us say the object is in B3. The newly predicted zone by the random forest is G1. The filter will determine the object is now in C2. Table III shows this filter increase significantly the accuracy of our system. Globally, it doubles the accuracy when compared to the raw data for all rooms. We reach a 60% of sequential accuracy in average. Still, the distance metrics remain high, indicating that there are many offset readings that increase the distances.

V. DISCUSSION

In the previous sections, we saw how we used our indoor positioning system to create an indoor tracking system. Before conducting these experiments, our hypothesis was that it would be easy to build a very accurate tracking system since our positioning system was really accurate for a sufficient precision. However, we saw in section IV that tracking is not really good with only the raw data. Even when the object is not moving, it is teleporting everywhere, moving all around the room. We discovered that the filter that affect the liberty of movement of the object had a better potential. By only allowing a moving of one zone at the time, the limiting filter was producing plausible paths, with many good sequences in them. It would take many consecutive bad readings to make this filter diverge from its correct path, reducing their effect even more than the moving average. Computationally, it is also a really fast filter O(1). The main reason explaining a lower

TABLE III. LIMITING FILTER ALONE

	Metric			
Room	***TZF***	***STZF***	***L dist***	***E dist***
Bedroom	0,797	0,653	124,775	2,297
Bathroom	0,886	0,660	236,350	5,732
Hall	0,814	0,711	64,800	1,218
Kitchen	0,863	0,567	248,500	3,720
Living room	0,913	0,753	207,250	2,143
Dining room	0,496	0,233	236,400	6,696
Average	0,795	0,596	186,346	3,634

accuracy than predicted is the human interferences. Indeed, the IPS was built from datasets built without any human in the smart home. When a human stands between the object and an antenna, the corresponding signal intensity is affected. It particularly affects DTs since the decision leading to a zone or another does not take the neighborhood into account.

VI. CONCLUSION

In conclusion, the system presented is capable of producing good indoor tracking accuracy while still being generalizable to other smart environments. This system is based on a qualitative indoor positioning system that uses zones of varying sizes. The main disadvantage of using decision trees instead of a classical localization method such as trilateration, for example, is that an error causes an unpredictable move, an unwanted teleportation. In our future work, our team will consider using larger size zones for the IPS and the ITS. The team is currently investigating the exploitation of qualitative ITS for the problem of activity recognition.

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