Qualitative RFID Tracking for ADL Recognition

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Abstract

In this paper, we propose a novel approach to perform activities of daily living (ADL) recognition using a tracking system based on the radio-frequency identification (RFID) technology.

Introduction

Population ageing is causing health related cost explosion (United Nations 2010). A solution is to age in place. But, to do so, we need houses that can provide basic assistance to its inhabitant. There are many challenges we face when trying to build a so called smart house (Han & al. 2014). One of them is creating a system capable of activity of daily living recognition. The main difficulty in such a system is the lack of granularity in recognized activities. This is sometime due to imprecision in sensors or sometime due to a lack of available information. We believe we can overcome those difficulties with a system based on objects tracking.

In recent years, many indoor positioning system (IPS) have been proposed using various technologies. The Radio Frequency IDentification (RFID) technology is a promising one (Yang 2012). There are three main families of algorithms that use RFID for indoor positioning.

The first family uses references tags. LANDMARC (Ni & al. 2004) was one of the first successful system built using RFID reference tags to provide positioning by comparing the received signal strength indication (RSSI) of a target tag with the RSSI of the references tags. Another approach is based on the trilateration technique. Trilateration make use of the RSSI to calculate a position with complex mathematical models. (Fortin-Simard & al. 2012) exploited those models to calculate the position of a tag with high precision. However, such models need to be precisely configured and tweaked. The third family of algorithms use data mining and other learning algorithms. (Yim 2008) used it with great success with wireless local area network access to determine a user's location.

Indoor Positioning System

As we previously mentioned, we want to create a system for ADL recognition using a qualitative IPS. By qualitative, we mean that our system provides a relative position and not precise coordinates. To build it, we first needed to create a special object with tags on it that could be used to train the IPS. This special object is a reusable bottle of water.

Once we had an object to locate, we needed to create the zones, the relative positions, we wanted our IPS to learn. To do so, we divided each room of a smart home into square zones of varying sizes. In the kitchen, zones are 40cm x 40cm; in the bedroom and the bathroom they are 60cm x 60cm; in the hall, the living room and the dining room they are 75cm x 75cm. The dimensions were chosen given the precision that was needed in each room for the tasks we want to recognize. After creating the zones, we recorded fifty RSSI readings in each of them, placing the bottle on a bench at the same height as the antennas, at about one meter high. This also corresponds to the height at which most human carry things in their hands.

In a final step, we used all those readings to train several classical classifiers. The results of this training are shown in Table 1. All classifiers have been obtained with the help of the well-known open source software Weka (Hall & al 2009), with default parameters. We did not want to try to optimize any classifier as this optimization would be influenced by the configuration of the apartment and not reusable. The models are: a Bayesian network (BNet), a multilayer perceptron (NNet), a 1 nearest neighbour (1-NN), a decision tree using the SimpleCart algorithm (Cart), a decision tree using the C4.5 algorithm (J48), a random tree (RT) and a random forest (RF)(Breiman 2001). There are many trees because they are fast to train and fast to use, which is important for a real-time tracking system.

Indoor Tracking System

In the previous section, we saw how we used classical leaning algorithms to create a qualitative indoor position system that uses zones instead of coordinates. In this section, we explain how we built an indoor tracking system (ITS) from this IPS. We first decided to choose to use a random forest of 250 trees as the classifier since that was the one with the best accuracy for a fast training. Then, we designed ten plausible paths in each room that we would want to track the bottle on, for a total of sixty paths (10 paths per room X 6 rooms).

One of the biggest issue we faced was that the bottle was often teleporting to aberrant zones due to interference or bad

Table 1: Accuracy for different learning algorithms on all datasets

Dataset	Accuracy						
	BNet	NNet	1-NN	Cart	J48	RT	RF
Hall	96,375	51,125	94,875	95,625	96,875	95,625	97,750
Living Room	97,657	91,257	94,800	92,400	92,057	89,314	97,600
Kitchen	95,691	83,491	96,891	96,400	96,418	96,709	98,891
Dinning Room	96,240	93,840	95,440	95,200	95,040	95,440	96,640
Bedroom	95,697	86,485	93,212	91,515	92,849	89,818	96,485
Bathroom	95,111	87,482	90,370	90,266	91,630	88,148	96,074
Average	**96,129**	**82,280**	**94,265**	**93,5678**	**94,144**	**92,509**	**97,240**

Table 2: Neighbouring filter with the weighted moving average using factorial

Metric	TZF	STZF
Bedroom	0,895	0,704
Bathroom	0,963	0,773
Hall	0,746	0,594
Kitchen	0,944	0,926
Living room	0,923	0,814
Dining room	0,826	0,723
Average	**0,883**	**0,756**

classification. To prevent this, we had to develop some filters. We first thought of a moving average of 10 readings to regularize the readings and the effect of bad readings. Then we weighted this moving average with different distributions (linear, factorial, exponential and logarithmic) and found that a slowly decreasing weight was best for regularity. But, there was still occasional teleportation. So, we designed a second filter that limit movement to a neighboring zone. Table 2 shows the accuracy obtained when combining the moving average and the neighboring filter. There are two metrics: the number of targeted zones found (TZF), and the sequential number of target zones found (STZF).

ADL recognition

In this section, we present some ideas we have for the actual ADL recognition. A promising approach is to use the interaction and proximity between objects to determine activities. Only by knowing what objects moved it should be possible to infer basic activities. Then, by knowing what are the last zones visited by an object we could predict what should come next, either by learning long sequences or by using an expert to build a library. To make our system independent from our lab configuration, we could also abstract the zones to name of the parts of a house, like *sink*, *oven*, and so on. Of course, given the size of our zones, it would mean that the new zone known as the *oven* in fact contains many distinct zones. We see it as an advantage as it also allows multiple objects to be considered at the same place when they are in fact right next to one another.

We also want to try to learn activities using sequences of names with simple, atomic activities like *boiling water*. A second learning phase would then be to learn macro activities using the previously learned atomic activities. All steps of this learning should be physically independent from the configuration of our smart home. For example, it should be easy to learn that taking a cup and coffee from the cupboard means *preparing coffee*. If it is not enough, we could also consider that a water recipient went from the sink zone to the coffee maker zone, and the action should become clear.

Using this simple example, we see that several activities do not need a complex and heterogeneous set of sensors to be recognized. We do not actually need to know that coffee maker is switched on and that water flown in the sink when location information of used objects is enough. In fact, these other sources of information could serve to increase precision on more complex activities rather than serve as the core of the system. Another simple activity to recognize could be *cooking eggs*. Then, we could combine those two (or more) to determine that someone is *making breakfast* and, thus, realizing complex activity recognition.

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