Analysis and Knowledge Discovery of Moving Objects Equipped with RFID Tags

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Abstract

Research on passive RFID localization has provided the community with increasingly accurate localization methods. In particular, it is now feasible to track tagged objects in a smart environment. While there is still room for improvement, the prospects of knowing where are the objects in real time have opened to new interesting questions and challenges. One of them is the analysis of the movement of such objects during the realization of daily life activities by the resident in order to extract interesting knowledge that could help understand the actions, the gestures and the context in which he evolves. In this paper, we present a new method based on well-known mathematical tools to analyze noisy positions obtained from a passive RFID localization system.

Introduction

Passive RFID technology has emerged as a very interesting solution for a multitude of problems where the technology involved requires to be non-invasive (small) and cheap. In particular, many researchers have worked toward the development of localization methods for robots [1], humans [2] and objects [3]. The research has led to an accrued interest by the smart home community which needs to find better methods to model the context of the environment (context awareness) and to recognize, and possibly learn, the Activities of Daily Living (ADLs) [4]. Especially, many researchers in this community aim to exploit the technologically enhanced houses in order to address some of the challenges due to the aging of the population. Toward that goal, a better exploitation of the data gathered on the environment is required, and higher level must be inferred from the raw information. Jakkula & Cook [5] were among the first to propose a transformation of the basic data to higher level. They proposed to extract the temporal relationships between events to learn representative models for the ADLs and to observe the same temporal relationships for the recognition. Following that train of thought, other researchers have proposed to exploit the spatial aspects in the realization of ADLs. For example, Augusto & Nugent [6] designed a spatio-temporal inference engine for smart home and more recently, Bouchard et al.[7] proposed to exploit topological relationships between entities to recognize ongoing ADLs.

Nowadays, many teams have implemented a passive RFID localization system to track the objects of their experimental environment in real time [3]. The accuracy and the precision of these methods have both improved to an extent which makes now possible for a multitude of new applications. For example, teams report precision ranging between 6-20cm, and other [8][9] have started to work on gesture recognition with RFID. Our team believes that a better analysis of the data collected from objects in movement could lead to improved Human Activity Recognition (HAR), context modeling, but also to help the data mining approaches to the challenges of smart home. In this paper, we present a new method that allows to infer high level knowledge that could be exploited to reduce the size of a data warehouse (Big Data) for easier data mining [10], but that could also be exploited for many applications. We present the method, and discuss those possibilities.

In the remainder of this paper, we present the novel method for the analysis of collected RFID signal in smart home. Then, we discuss the type of knowledge that can be extracted from the result of our analysis. Afterward, we present a set of experiments that were done exploiting simulation software specifically developed to generate gestures with a random noise. The method was used to perform recognition of a simple set of gestures, and the

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results are presented in comparison with the literature. Finally, the paper concludes with a presentation of the related work and an assessment of the new method.

RFID Analysis Model

The first thing that needs to be discussed before presenting our new model is the passive RFID technology used for the localization of objects. While in this paper we do not contribute to the challenge related to this particular application of the technology, an explanation of the context is important to understand the difficulty of extracting high-level spatial knowledge. Passive RFID technology works without the use of battery (which is essential in assistive smart home) and by exploiting tags that remain in a dormant state. The tags are waked by the reception of a radio-wave emitted by a nearby antenna, and they exploit the energy of that wave to emit their unique identification. The localization of such a tag is, then, generally performed by exploiting the Received Signal Strength Indication (RSSI) and a software model to perform a type of trilateration or, more rarely, triangulation.

One of the main issues is that the RSSI is strongly affected by any perturbations and thus can lead to a lot of bad localization data. For example, interference from metal pieces, humans or emission from another technology can completely disturb the process. Moreover, it is not uncommon for RFID system to produce false-negative readings. Due to these problems, passive RFID localization is still very challenging despite the enormous amount of research that was done during the previous decade.

Keeping in mind the challenges and issues; we developed a method to analyze and extract high level knowledge from noisy dataset of positions of a moving object. One of the goals is, for example, to be able to understand the gestures performed by a human subject. We discuss later in the paper the possibilities of the method. The figure 1 shows the general idea we developed. The first step is to cumulate a minimal number of positions from a tagged object. Then, the model exploits polynomial and linear regressions to analyze the dataset. The dataset must be managed carefully for better results (direction on abscissa, size, etc.). Thereafter, the new found polynomial is derived, and the roots are found. Finally, the high-level knowledge can be extracted.

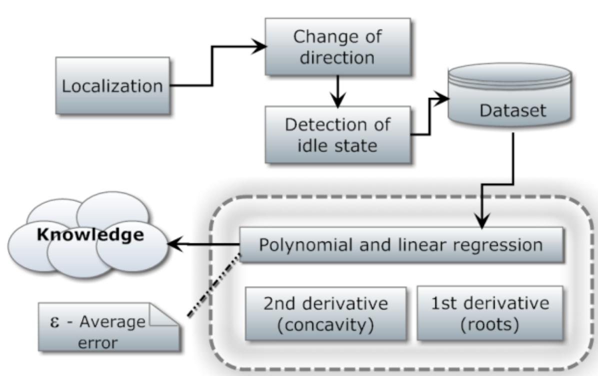

Fig.1 General architecture of the method.

Data management

The data collecting step is important since we need to be able to recognize two things. First, it is required to understand when the object is *Idle* because the position could cumulate in a cluster and reduce the accuracy of our method, which performs regressions. To do so, the dataset is divided into two halves. For each part (begin and end) Cartesian coordinates are exploited to calculate an average position of the object in real time. Then, the two averages are compared, and a distance is found. That distance is a key point since whenever it is over the average error of the localization algorithm, the object is considered as currently moving. When an object is already moving, the same method is used to test if it returned in an *Idle* state. However, only the recent data is considered for the average. While the recognition of the *Idle* time is not mandatory for our regression based method to work, it is very useful to get the knowledge on the state of each object in a smart home.

The second part of the data management is to limit the growth of the dataset and distinguish the direction of the moving object on the abscissa. In our implementation, the dataset is limited to periods where the object is moving only in one direction on the abscissa. Therefore, if the object enters into an *Idle* state or if it changes direction on the abscissa, the dataset is reset and the knowledge extracted from the regression is stored for further usage (by an HAR algorithm, for example). To recognize the direction of the movement on the abscissa, a moving average is computed on the last second of the abscissa coordinates. If the moving average changes of direction (increasing or decreasing), it means that the objects have begun to move on a different way on the abscissa. The Fig. 2 illustrates why it is important to recognize the changes of direction on the abscissa with a fictive polynomial regression. As it can be seen, without distinguishing between the two datasets, the polynomial regression is distorted and does not represent the movement in a sequential manner.

Mathematical tools

The previous section explained the premise of the data management for our method to be optimal. This section explains the mathematical foundation for the analysis of the movement and the knowledge inference. First of all, it

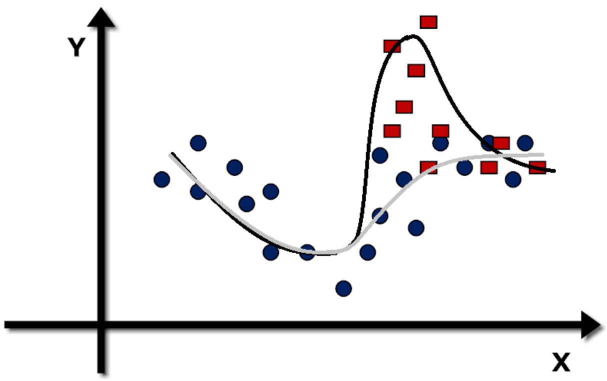

Fig.2 The circles represent the movement increasing on the abscissa with the grey line being the accurate polynomial. The rectangles are the positions decreasing on the abscissa, and the black line shows how the polynomial become inaccurate.

is supposed that a dataset of n consecutives positions in the form (x_i, y_i) for $i = 1, \ldots, n$ is collected. In order to model as best as possible the trajectory of the movement executed by the hand, we use the polynomial regression technique. Very often, hand movements are not linear but nonlinear and, thus, linear models are unsuitable.

Polynomial regression consists in finding the polynomial that best fits the data. The technique is based on the well-known least-squares method. The goal is to find the polynomial of degree k less than n (the numbers of position readings) of the form:

$$Y(x) = b_0 + b_1 x + \cdots + b_k x^k \tag{1}$$

which minimizes the least-squares error. A rather naive way to do so, is to suppose that the degree k of the polynomial is $n-1$ since it is always possible to pass a polynomial of order $n-1$ through n points and, next, to proceed to the resolution (finding the values of the coefficient b_j for $j = 0, \ldots, k$) of the following matrix equation illustrated in (2).

$$\begin{pmatrix} n & \sum_{i=1}^{k} x_i & \cdots & \sum_{i=1}^{k} x_i^k \\ \sum_{i=1}^{k} x_i & \sum_{i=1}^{k} x_i^2 & \cdots & \sum_{i=1}^{k} x_i^{k+1} \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{i=1}^{k} x_i^k & \sum_{i=1}^{k} x_i^{k+1} & \cdots & \sum_{i=1}^{k} x_i^{2k} \end{pmatrix} \cdot \begin{pmatrix} b_0 \\ b_1 \\ \vdots \\ b_k \end{pmatrix} = \begin{pmatrix} \sum_{i=1}^{k} y_i \\ \sum_{i=1}^{k} x_i y_i \\ \vdots \\ \sum_{i=1}^{k} x_i^k y_i \end{pmatrix}. \tag{2}$$

This matrix equation can be easily solved by using Java scientific library [11] or any mathematical software such as Maple, Mathematica, R, etc. Usually, the degree k of the regression polynomial should be as low as possible to obtain the best fit. Therefore, statistical tests, namely the F-tests [12], are performed between the different models in order to find the best degree k of the polynomial. It is worth noting that the polynomial obtained by the polynomial regression method should not be used to extrapolate data beyond the limits of observed values.

The best polynomial alone does not give very interesting information; therefore, we must look forward analyzing the function obtained. To do so, we search to identify the vertical changes in the movement. This can be achieved by executing the second derivative test which one provides information about the concavity of a function at different points of the curve. In fact, it is well-known that, in calculus, the second derivative test is used to determine whether if a given critical point of a real function (a polynomial of degree k in our case) is a local maximum or a local minimum. The test is defined as follows:

If a function $f(x)$ is twice differentiable at a critical point x (i.e.$f'(x) = 0$), then

- If $f''(x) < 0$, then f is concave down at x.
- If $f''(x) > 0$, then f is concave up at x.

Consequently, we must find all the critical points, which are points where the first derivative of the function (polynomial of degree k in our case) vanishes at these points. Differentiation of a polynomial of degree k, say $P_k(x)$, yields a polynomial of degree $k-1$, say $Q_{k-1}(x)$ which implies that we need to solve the following equation:

$$Q_{k-1}(x) = 0 \tag{3}$$

in order to find all the critical points of the curve. Since a polynomial of degree $k-1$ possesses $k-1$ roots and that it is impossible to find analytically the roots of a polynomials of degree higher that 4, we must employ a numerical method to approximate the roots. The numerical method employed to accomplish this task is the Laguerre's method [13] which is performed by executing the following algorithm:

Let $P_k(x)$ be a polynomial of degree k. Then to find a first root of $P_k(x)$ do:

1. Choose an initial guess x_0
2. For $k = 0,1,2, \ldots$ do

- Calculate $G = \frac{p'(x_k)}{p(x_k)}$
- Calculate $H = G^2 - \frac{p''(x_k)}{p(x_k)}$
- Compute $a = \frac{n}{G \pm \sqrt{(n-1)(nH - G^2)}}$,
  where the sign is chosen to give the denominator with larger absolute value
- Set $x_{k+1} = x_k - a$

3. Repeat until a is small enough

If a root has been found, say r, then divide $P_k(x)$ by $(x - r)$ to obtain a polynomial $Q_{k-1}(x)$ of degree $k - 1$ and restart the procedure.

It is noteworthy to mention that the k roots obtained after having performed this algorithm must be examined carefully. Among them, some can be complex roots and, thus, have no physical significance for our purpose. Therefore, we only consider the real roots obtained by applying the Lagrange's method. Finally, each of these roots (critical values) is used to determine the concavity of the curve (movement) at these points. This task is done with the help of the second derivative test explained above. All the different steps described in this section allow us to obtain a general idea of the movement of the object. Obviously, some other properties of the polynomial curve could be exploited, and that is exactly the goal of the method, to provide a tool for the inference of high level knowledge adapted to any application.

Knowledge Extraction

The analysis of the presented method could be used in various ways. In this subsection, we will overview some of them. The most intuitive application would be to represent steps of fine grained activities by a limited set of movements. One of the representation methods could be to represent it by a sequence of concavity up or down combined with the distance between the roots. The Table 1a shows such a representation with qualitative distance. Another example of representation (which is tested in this paper) would be to transform the polynomial into a sequence of basic qualitative direction with our without distance such as illustrated by Table 1b. The extraction of this knowledge could be very useful. For example, gestures could be learned and recognized with such a method. Data mining algorithms could also be exploited to find repetitive patterns over a training set of several ADLs.

a	$\mathbf{2 \cup 4 \cap 2 \cup 8 \cap 3}$
b	$\mathbf{3 \leftarrow, 2 \uparrow, 4 \leftarrow, 1 \downarrow, 1 \rightarrow, 2 \downarrow}$

Table.1 Examples of knowledge representation.

Another application could be to monitor the performance of a resident in his daily task. To do so, one could collect a dataset of an action (e.g. pouring milk in cereals, moving a cup of coffee between two positions, etc.) that would be repeated a few times in order to obtain a representative model. Then, our new method could be applied to obtain a polynomial which would be saved. By comparing the polynomial when the user repeats that action, we could be able to diagnose degradation in his performances. Obviously, much still need to be done for such an application to be implemented in a realistic context, but we think our method open to very interesting perspectives.

Validation

To validate our new method, we developed new software that can generate gestures and sequence of gestures with various parameters. The simulator takes into account an average error, which was set at 10cm, and uses it to generate noise in the output data. The user must specify the length of basic gesture in cm and the speed of the generation of data. We based our parameters value on the work of Bouchard et al. [9] and Azadazeh et al.[8] and therefore, the movements were composition of eight basic directions (North, NorthEast, East, SouthEast, South, SouthWest, West, NorthWest). One position was generated every 20ms and a random noise exploiting the average error was added to the position. For example, if the object should be at (10, 0) and the error is $\pm$10cm, then the generated position would be $(0 \leq x \leq 20, -10 \leq y \leq 10)$. The Fig.3 shows an example of dataset with a generated polynomial best fitting the data.

For the tests, we let the generator select randomly the directions. The recognition was done on the sequence of directions when the dataset was reset because of a change

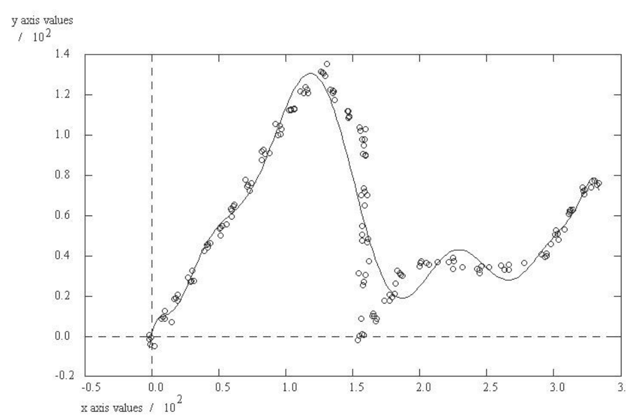

Fig.3 A polynomial representing the randomly generated directions. For better clarity, only the average positions (1/10) are represented.

on abscissa or because the object became *Idle*. The basic directions are extracted from the polynomial by comparing the roots obtained. When the variation between two consecutive roots is important, a line is traced and the angle versus the abscissa is computed. With the angle, it is then straightforward to determine the basic direction. It is noteworthy to mention that if the movement on the abscissa is negative, the inferred directions must be mirrored. If, on the opposite, the variation between two consecutive roots is small, the comparison is made with the next on the list.

We let the algorithm, and the generator run for approximately 120 basic gestures. Then, we compared the output sequences with the generated sequences. We divided the results by the length of the generated directions. The Table 2 shows the results of the classification using the method implemented.

Length	$\approx 20cm$	$\approx 30cm$	$\approx 40cm$	$\approx 50cm$
Percent recognized	40%	77%	83%	80%

Table.1 Percent of accurately classified directions.

The first thing to notice is that except for the directions of approximately 20cm, the length does not seem to affect the accuracy. At first, we supposed it would, since in the literature the length is the single most important characteristic for gestures recognition with noisy data. Obviously, others aspects are important such as the number of element in our dataset, but in our case, it was not an issue. It is also not surprising that the success of the recognition is disappointing for the smallest directions, since the average error in positioning is 10cm. In that context, it would prove difficult to do even for a human visualizing the dataset. Finally, many of the misclassifications are between two consecutives perpendicular directions and a diagonal one. For example, on the Fig.4, the sequence of directions is East, North, SouthEast, but the inferred sequence is NorthEast, SouthEast. This kind of misclassifications is usually not damageable since the meaning remains unchanged. In conclusion, the performance of the method applied to the recognition of basic directions is fairly good and encouraging for the future.

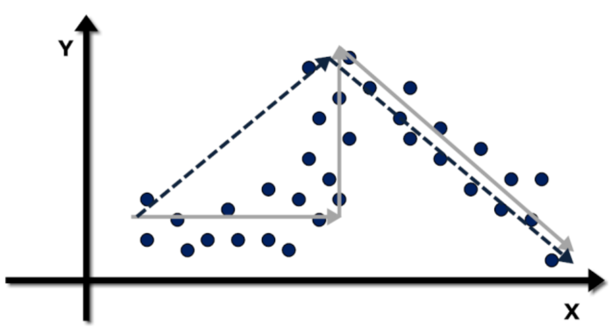

Fig.4 Error in classification of the directions. The dashed arrows represent the inferred directions versus the real directions.

Related Work

It is not the first time that passive RFID technology is viewed by a team of researchers as a key technology to address the challenges related to assistive smart home (HAR, context modeling, etc.). One of the majors and earlier works have been conducted by Patterson et al. [14]. In their work, they exploited special gloves destined to be wear by a smart home resident during his daily life activities. These gloves are equipped with a small RFID antenna capable of detecting RFID tags within two inches of the palm. They implemented a model based on the Hidden Markov Machine (HMM) which was using key objects aggregation. With it, they were able to recognize fine-grained ADLs. The main problem of their approaches is the requirements for the user to wear two gloves at all time.

More recently, Azadazeh et al.[8] proposed to address the challenge of human-computer interaction with gestures by exploiting passive RFID technology. With three antennas on a desk, they monitored an 80cm by 80cm area, which was divided into 64 equally sized square cells (10cm by 10 cm) and localized using reference tags. Their system is based on few important assumptions. First, it is fast enough to never miss any cell in a sequence; that is, the tracked object cannot move farther than one cell away in between two readings. Second, only forward local moves are possible. Their algorithm cannot recognize two consecutive gestures (no segmentation) but works well (93% recognition) on a dictionary of twelve gestures. Their work showed that there is potential for gesture recognition with passive RFID.

The team of Bouchard et al.[9] followed the footsteps of Azadazeh et al.[8] and proposed a vector based solution to the problem of gesture recognition. In their work, they aimed to extract basic gestures (that they called atomic) and understand the ongoing ADLs in a smart home. Their work exploited well-established knowledge from qualitative spatial reasoning and allowed them to recognize 78-91% of very simple gesture. Similarly, to Azadazeh et al.[8], they did not try to analyze a big dataset of position to extract high level knowledge. The gestures recognized also need to be long. They reported a length between 40 and 80cm.

All these approaches are interesting, but they suffer from fundamental limits. In comparison, our method is more general and could be used for a larger variety of applications. For example, in the future, the result could be used for complex ADLs representation or to monitor the performance of a user in the execution of specific movements.

Conclusion

In this paper, we have presented a novel method to analyze the imprecise and noisy dataset of positions extracted from a passive RFID localization system. Our method is flexible since it can be adapted to other technology and only requires inputting the average error as a parameter. The method is based on well-known mathematical methods enabling to find the best polynomial fitting the data and finding the roots from the Laguerre's method by deriving the polynomial. We have performed a first set of experiments with one potential application of our new method by exploiting simulation software that generates gestures. The method returned good results varying from 68-90% depending on the length of the generated gesture. As we explained, the polynomial could be exploited for other purposes than extracting qualitative directions of a moving object. In the future, we aim to develop those potential applications and implement test in a real smart home setting.

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