An Indoor Localization System Based on Artificial Neural Networks and Particle Filters Applied to Intelligent Buildings

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Abstract

Intelligent Buildings comprise a key part within the Smart Spaces field, providing users with seamless, invisible and proactive services adapted to their preferences and needs. Provided services in Intelligent Buildings can be offered intelligently if one considers the static and dynamical status of the building and the location of users. To face all of these issues, it is necessary to acquire contextual information, both from users and the environment, in a nonintrusive and natural way. Gathering data about the identity and location of occupants enables more personalized services, while wasted energy in overuse is reduced. In this work we propose a low-cost and nonintrusive solution to solve the indoor localization problem, focused on satisfying the requirements in terms of accuracy in localization data needed to provide customized comfort services in buildings, such as climate and lighting control or security, with the goal of getting saving energy while ensuring comfort. The proposed localization system is based on RFID (Radio-Frequency Identification) and IR (Infra-Red) data. The solution implements a Radial Basis Function Network to estimate the location of occupants and a Particle Filter to track their next positions. This mechanism has been tested in a reference building where an automation system for collecting data and controlling devices has been setup. Results obtained from experimental assessments reveal that, despite our localization system uses a relative low number of sensors, positions obtained are really accurate considering the requirements in terms of precision in localization data to provide pervasive services to occupants in buildings.

Keywords:
indoor positioning, smart building, RFID, artificial neural networks, particle filter

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1. Introduction

In the last years, the research on Smart Spaces has evolved in real solutions that improve the indoor life thanks to innovations on sensors/actuator integration and control processes, among others, but more recently, thanks to information and communication technologies.

A smart space aims to provide seamless, invisible and proactive services adapted to our preferences and needs. A great contributor for all these changes has been the Internet of Things (IoT) [1] field, which considers pervasive infrastructures of fixed and mobile heterogeneous nodes designed to obtain a greater integration and accessibility.

Smart Buildings is considered a research field within smart spaces, which is growing in interest due to whole time people spent indoors daily. According to experts in this field [2], an intelligent building is one that provides us with a productive and cost-effective environment, through optimizations based on three basic elements: people (considering owners, occupants, visitors, etc); products (standing for materials, fabrication, structure, facilities, equipments and services); and processes (composed of automation, control systems, maintenance and performance evaluation).

Moreover, it is important to consider that buildings are one of the most important energy consumption points, both residential and commercial [3]. Improving energy efficiency is the cornerstone of many administrations around the world nowadays. It implies improving the interaction between building systems and users, reducing energy consumption, and therefore, CO_2 emissions. Automation Systems are essential for this issue, as it is remarked in [4]. These systems take input data from sensors deployed in corridors and rooms (presence, light, temperature, etc) [5] and use this information to control certain subsystems, such as heating, ventilation and air conditioning (HVAC) or security. In order to control these subsystems, an intelligent management must provide the proper adaptability to both the environment and users, to cope with the most important comfort and energy efficiency requirements [6].

As it can be noted, location plays an important role in this kind of context-aware applications, since for a vast number services offered in a smart building, it is necessary information about the presence and location of users. Their identities could be also needed to deploy customized services. However, depending on service requirements in terms of accuracy in the location data about users, a different localization scheme could be applicable, varying the number of needed sensors and the algorithms used.

There has been a great technological progress on indoor localization systems in recent years. But most of the proposals do not solve fully problems such as the time required in the calibration process, poor robustness or high installation and equipment costs [7].

The work presented in this paper proposes a low-cost and nonintrusive solution for the localization data needs of the most important subsystems of a smart building, i.e. lighting and HVAC, with the goal of achieving offer personalized and environment friendly services.

The proposed location mechanism integrates RFID (Radio-Frequency Identification) and IR (Infra-Red) data for computing the user position. The RSSI values are used for estimating inter-tag distance, and a Radial Basis Function Network has been developed to carry out the estimation of user locations. On the other hand, a tracking method based on a Particle Filter algorithm has been developed to infer the next positions of the user. This localization system meets the accuracy, cost and complexity requirements of our indoor services, while the number of devices used by the location mechanism is optimized.

The structure of this paper is as follows: in Section 2 background information about intelligent buildings, energy efficiency and indoor positioning is reviewed. Section 3 presents the proposed indoor localization system based on artificial neural networks and particle filters. The experience deploying and the tests performed of the system are discussed in Section 4. And, finally, the conclusions are collected in Section 5.

2. Background

As has been said, the framework of the indoor localization system presented in this work is in the context of building. Given that the final purpose of our work is coming up with an intelligent and energy efficient building, the proposed localization mechanism must meet certain requirements in terms of position data accuracy, cost, flexibility and scalability. In the first point of this section we present the context of our problem and the location data requirements of our system, given the most important energy performance features in a building. Finally, in the last part of this section we review the most relevant localization technologies treated in the literature and present our location solution.

2.1. Building Management Systems for Energy Efficiency

An indoor intelligent management system must be able to provide monitoring and automation capabilities to cope with most important comfort and energy efficiency requirements [6]. In addition, a suitable comfort level is desired for guaranteeing thermal, air quality and luminance requirements of occupants. Therefore, energy savings should be addressed establishing a trade-off between comfort measures and the energy resources required. The aim of these systems is, first, offering a real solution to monitor energy consumption of the most important subsystems of a reference building, i.e. lighting, HVAC and most energy consuming appliances; second, assess energy efficiency by computing significant parameters based on the collected monitoring data; and, third, achieving a comfort level committed to energy efficiency requirements. This last part is essential, and it is carried out by taking intelligent decisions to save energy and considering different comfort levels for occupants.

During these phases it is necessary to continuously re-engineer in real time the index that measures energy efficiency to adapt the model to the building conditions. However, the optimization of these parameters comprises a complex task, full of variables and constraints. For instance, a multi-criteria decision model to evaluate the whole lifecycle of a building is presented in [8]. This problem is tackled from a multi-objective optimization viewpoint in [9], and it concludes that finding an optimal solution is unreal, being only feasible an approximation of it.

Although there are many works related to Building Management Systems (BMSs), a lot of them have failed to fully optimize energy consumption in real time, and when the BMS is not working adequately, a great amount of energy could be wasted due to excessive heating or cooling, for instance. In [10], an examination of the main issues in adaptive BMSs is carried out, however, as it is stated, there are few works dealing with this problem completely.

The long-term goal of all energy efficiency measures in the literature is reaching a net-zero/positive energy building (NZEB/PEB) [11], where the power consumption will be null or even negative, thus generating energy that can be stored or sold to energy providers. In this kind of systems the availability of alternative (and green) energy sources is essential. Nevertheless, there is a number of parameters that cannot be a priori ascertained during operational conditions: unpredictable user actions, opening and closing of windows, weather conditions, fluctuations in energy price, etc. Therefore, although there are many investments in smart building technology, the research area of using real-time information is in a relatively immature state, since static and dynamic information, as long as energy saving and user comfort objectives, should be considered together to accomplish a successful design [10].

The impact of the HVAC consumption in the total energy used in buildings is extremely important, comprising 50% of the building energy consumption, and in many developed countries it represents 20% of the total energy consumption [12]. The European Commission has recently issued a recast of the Directive about Energy Performance of Buildings (2010/31/EU) [13], which pushes for the adoption of measures to improve the performance of the energy used in building appliances, lighting and, above all, HVAC systems. The CEN's standard EN 15251 [14] specifies the design criteria to be used for dimensioning the energy system in buildings and how to establish and define the main input parameters for building energy estimation and long term evaluation of the indoor environment (thermal and visual comfort, and indoor air quality). Among others, several parameters involved are: location data about occupants, user activity level, total number of occupants per room, temperature, humidity and natural light. All these variables need to be measurable and available from the automation system deployed in the building.

Therefore, the need of solving the localization problem inside the building is clear, to determine the user location, the human activity level and the number of occupants. It is necessary to gather localization information, as well as user identity data, so that an Intelligent Building can learn and manage devices according to the behavior of users.

Although solving the user identification issue in smart buildings is a key objective, privacy should be considered. Some sensors cannot be installed in buildings, for instance, in Spain video cameras could not be used in offices. These problems cause some localization systems to be unsuitable in

Intelligent Buildings, where nonintrusive, ubiquitous and cheap systems are needed. In addition, maintaining an updated image of the operation environment is essential for indoor localization systems. Therefore, in order to offer comfort and energy efficiency services, our localization system must be able to locate a user among the various areas of the building, depending on the needs of lighting and HVAC services, for instance, and thus our localization system should be able to calculate the user position within target regions of different areas.

2.2. Indoor Localization Problem

There is a common classification of indoor localization solutions in the literature: those based on RF and those using other technologies. Among RF-based techniques we could cite those based on GPS, wireless local area network (WLAN), and RFID localization, whereas non RF-based techniques include audio, visual, ultrasonic, infrared and laser sensors. By nature, RF signals have certain advantages over non-RF signals, as it is explained in [15], since despite that non RF-based localization tecniques are relatively mature, they are vulnerable to environment disruptions. Depending on the accuracy needs of the final localization application, a specific technological solution should be chosen to solve the problem.

In [16], for instance, a localization mechanism based on 802.11 and RADAR technologies is presented. Its main advantage is the easy deployment but a delicate calibration process is needed. In [17] an RFID localization mechanism is proposed, enabling 3D localization, but presenting important errors due to the RFID signal variations during its indoor transmission. In [18] a fusion of infrared and active badge data is used to calculate the position. Although this is a low-cost solution, an imprecise location estimation is obtained using this type of localization technology. In [19] a localization mechanism based on cameras is proposed. Wearable devices are not needed in this solution, but a high cost and a delicate calibration process are its main drawbacks.

Since each localization technology has its pros and cons in terms of accuracy, cost and complexity, the fusion of several of these technologies should improve the overall system performance. Moreover, in our localization system we need to deal with both the identification and privacy problems, avoiding the common intrusion problem of cameras.

Among the various localization technologies previously mentioned, RFID and infrared (IR) have been chosen. RFID provides identification capabilities inherently and extra security features could be added to deal with the privacy issue. Furthermore, the relatively low cost of RFID tags makes this solution a popular candidate to deal with localization and tracking needs, despite the drawbacks of imprecise location estimate due to RFID signal variations, as it is indicated in [20]. Additionally, a lot of public and private buildings already provide access control through personal identification based on RFID, which implies a cost reduction in the system deployment. The same applies to the IR technology, used in automatic control in alarm systems. Using any of these two technologies to solve the indoor localization problem means a cost saving, since no additional devices are needed in those buildings where these devices are already presented. Additionally, using IR sensors we can provide stability to the localization solution since it is a non-RF based technology, and thus it is not influenced by the losses for reflection, diffraction and absorption in walls, floors, etc.

Location technologies based on RFID can be classified into three categories [21]: tag-based, reader-based and hybrid. In a previous work [22], we present a theoretical study about the indoor transmission of RFID signals given a real distribution of reference tags. From this, we propose to carry out the fusion of RF-based data and non RF-based data in order to solve the large variability problem of the RFID signals in indoor environments. Furthermore, using these theoretical analysis, it is possible to optimize the number of devices needed to solve our location problem.

In contrast to many RFID location-based works, where it is common to use information from several RFID readers to improve robustness through integrating beaconing information from multiple sources [23], our localization system can work with a single RFID reader to reduce cost. Location robustness is offered by a mechanism that combines RFID and IR data in an effective way. It is important to note that IR devices are cheaper than RFID readers. In [20], for example, a solution that also combines RFID and seamless sensors solves the localization problem by means of an agent-based virtual architecture that considers human-centric needs. It calculates the probabilities of possible user paths choosing a locator region to represent the user position. In contrast to this paper, our work is based on estimation and tracking techniques that let us achieve an efficient solution, while cost considerations are also taken into account through the optimization of the number of sensors used.

3. An Indoor Localization System Based on Artificial Neural Networks and Particle Filters

This section explains the analysis performed to give an optimum solution for the localization problem, as well as the algorithms used to process the gathered data from the RFID and IR systems to compute the user positions.

3.1. Theoretical Distribution of the RFID Signals in Indoor Environments

It is known the large variability problem of the RFID signals in indoor environments [23], which implies that to solve localization problem using RFID data may derivate in inaccurate estimations of the user positions.

Despite this, as mentioned previously, RFID system provides some advantages and its relatively low cost makes this a good solution to deal with localization and tracking needs, and being more often to find this technology already deployed in modern buildings (such as access control systems).

Bearing all these aspects in mind, we bet to use RFID technology while a theoretical study about its indoor transmission is performed (given a real distribution of RFID reference tags). We aim to analyze the RFID signals distribution in indoor spaces, i.e. the RFID power losses through reflection, diffraction and absorption, and to provide the most suitable technological solution to solve the localization.

This theoretical study was carried out using a radio planning software tool, which is able to consider different propagation models to simulate the RF signals transmission. In our study, we considered an indoor RFID signals transmission based on the application of Geometrical Optics (GO) and Uniform Theory of Diffraction (UTD) using ray tracing techniques. With this method it can be predicted the electric field created by the direct, reflected and diffracted contributions of RFID signals. Then, as parameters required to carry out these simulations are the reflection, diffraction and absorption coefficients of walls, ceiling and floor. Thus, when we performed these studies, we took into account different values for these coefficients, and then, our final theoretical proposal for solving the localization cover this issue. More details about this theoretical study are presented in [22].

This proposal consists on performing the fusion of RF-based data and non RF-based data to solve the large variability problem of the RFID signals. Thus, we propose to locate the non RF-based devices in a such way that lets divide the total area into subareas where RFID distribution is uniform, choosing the best locations for non RF-based devices analysing this distribution. Therefore, the active RFID reference tags are installed in the ceiling of each subarea, and then, the RFID information inside the subareas is used to further localize the user located inside of it, being possible to implement a regression or classification technique to estimate the location data of occupants taking into account these subareas.

In the following subsections, the different stages of the localization mechanism proposed are quite explained.

3.2. Overview of the Localization System

As it has been already mentioned above, the technological solution to cover our localization needs is based on a single active RFID system and some IR transmitters. The RFID technology provides cost and identification advantages, while the IR technology provides stability to the localization mechanism, since IR transmitters provide us information related to which region a target tag belongs.

The integration of these two technologies in a final and commercial system is already available. Thus, all the RFID tags used are IR-enabled tags, whose IR sensor is powered by an IR transmitter. The RFID tags communicate with a nearby RFID reader, reporting on from what IR transmitter is reading.

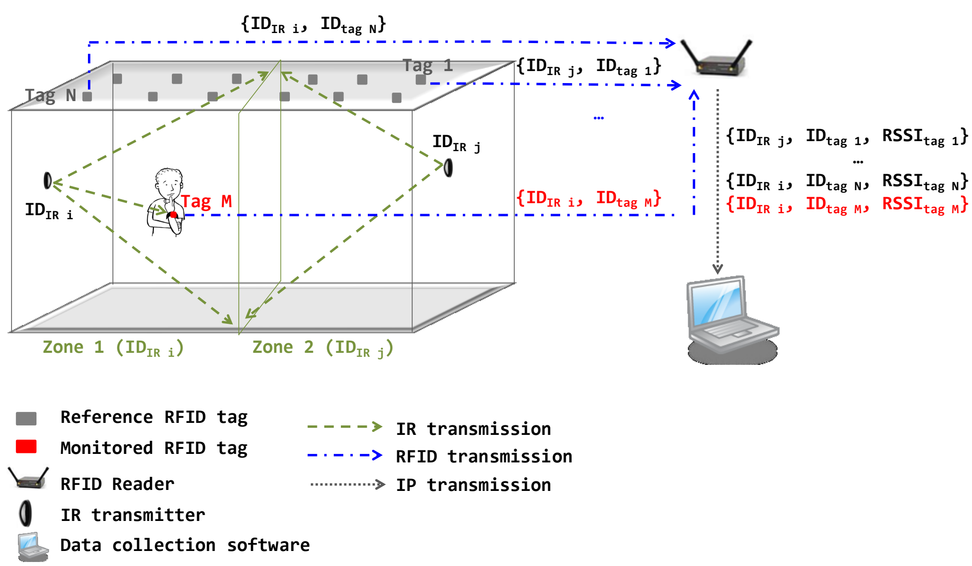

Figure 1: Scenario of the localization solution using RFID and IR devices

Figure 1 illustrates the data exchange of our localization system, where the RFID reference tags are placed in the ceiling of the room, the IR transmitters are placed on the walls and the target user wears the RFID monitored tag.

In detail, the process is as follows: the RFID reader receives a data vector from the IR-enabled RFID tags periodically (after several seconds), this vector contains $[ID_{ir}, ID_{tag}]$, where ID_{ir} is the identifier of the IR transmitter that is read by the RFID tag with identifier ID_{tag}. Additionally, the reader is able to provide us with the Receive Signal Strength Indication (RSSI) related to this tag. This data are continually updated, hence, the dynamics of the environment can be modeled continuously. Then, the input data of our localization mechanism are vectors in the form $[ID_{ir}, ID_{tag}, RSSI_{tag}]$, which are obtained from the RFID reader.

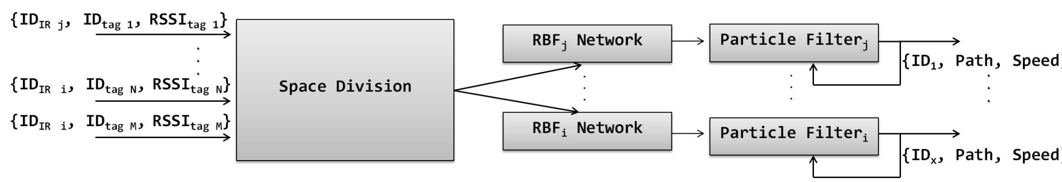

Figure 2: Schema of the data processing for position calculation

Figure 2 shows a schema of the data processing implemented to solve our indoor localization problem, which can be split into three stages that are explained in the following subsections.

3.3. Space Division through IR Transmitters

Our goal is to get an easily trainable localization model to compute the relationship between the RSSI values and the objects positions. Since the RSSI data are not robust, due to the multi-path phenomenon, we first bound the area in which the user stand by dividing the space in IR zones. This is performed according to the ID_{ir} values received. Each of these ID_{ir} values is associated with some ID_{tag} and $RSSI_{tag}$ values coming from several deployed active RFID reference tags installed in the ceiling of each subarea. Then, the information inside the subarea to which the monitored tag belongs is used to further localize the object.

3.4. RBF Algorithm for Location Determination

The following stage after the space division consists on exploiting the reference tags RSSI database selected in the first stage to approximate the function that maps the reference information from the signal space to coordinates in the plane by interpolating the collected data.

A widely used solution is applying the *Nearest Neighbors Technique* to choose the reference tags used to estimate the target position, but this technique provides a poor estimation due to the great variations of the RFID signals. An alternative solution is using *Artificial Neural Networks (ANN)* [24] [25] for that purpose, where localization can be viewed as an approximation function problem. Thus, for instance, in [26] a modular classification model based on modular multi layer perceptron (MLP) networks is presented to develop large scale and highly accurate signal strength based location systems.

The work presented here uses the *Radial Basis Function (RBF)* technique, which is a special class of ANN. Some advantages of RBF are its scalability and easy deployment for different RFID system setups, where a variable number of RFID readers or reference tags (fingerprints) may be available. Then, for each space division performed according to the ID_{ir} values received, a radial basis function (RBF) network can be implemented as a regression technique to estimate the position of the monitored tags.

This mechanism can be summarized mathematically as follows. The input space P of our RBFs is the vector of RSSI values received in the RFID reader. These data can be denoted as:

$$P \in R, P = \{p_i\}, \forall p_i = \left[p_1, p_2, \dots, p_n\right] \tag{1}$$

Where n is the number of reference tags within the chosen subarea. The target class Z represents the positions of the reference tags. This is denoted as:

$$Z \in R^k, Z = \{z_i^k\}, \forall z_i^k = \left[z_1^k, z_2^k, \dots, z_n^k\right] \tag{2}$$

Where k is the dimension of the position of the reference tags. In our case, we assume a value of $k = 2$, then given the training values $\{(p_i, z_i^k),\dots,(p_n, z_n^k)\}$, our goal is to find a function that let us classify the tracking tag position ($z_i = [x_i, y_i]$) knowing its RSSI tag value (p_i).

The RSSI tag value p_j is provided as input to all functions of our RBF classifier, and the output $f(p_j)$ is given by:

$$f(p_j) = \sum_{i=1}^{c} w_i \cdot \varphi(\parallel p_j - c_i \parallel) \tag{3}$$

Where $\parallel p_j - c_i \parallel$ is the Euclidean distance between p_j and the RBF function with center c_i. The number of RBF is C, and w_i are the weights of the network. Gaussian radial basis are usually used to represent the RBF. However, other types of functions are common, such as thin-plate splines, multi-quadratic, linear polynomial bi-harmonic splines, etc. [27]. The poly-harmonic splines are softer, and we use these functions for our RBF networks. The equation that represents to this type of functions is shown in Eq. (4).

$$\varphi(\parallel p - c_i \parallel) = \parallel p - c_i \parallel^{\beta} \log(\parallel p - c_i \parallel) \tag{4}$$

The value of β specifies the width of the basis functions and allows their sensitivity to be adjusted. When β decreases implies that the basis functions become wider and there may be more overlap among them. The appropriate value of β is usually selected experimentally based on the reference data, and can be further adjusted when testing data are available. A common practise is to use a heuristic method to set the width β according to Eq. (5), where $d_{max} = \parallel p_j - c_i \parallel$ for $i = 1, ..., L$.

$$\beta = \frac{1}{2 \cdot d_{max}} \tag{5}$$

From this equation, it is deducted that when the distance among centers in the n-dimensional signal space increases, the value of β is reduced to ensure that the basis functions still overlap enough to produce accurate location estimates. With this scheme the value of β can be easily adjusted to provide high level of accuracy when a variable number of reference tags is used

The proper values for C and the centers c_i are not trivial. These values affect the performance of the RBF network. A common practice is using each reference RSSI value to define the centers, so if there are L reference tags, there will be L basis functions. However, this architecture has high memory requirements when there are a lot of reference fingerprints and when there are more than one RFID reader. In these cases the computational complexity is high, both for the calculation of w_i and location estimation. In our problem, the number of reference tags per each space division performed is low and a single RFID reader is used, therefore there are no problems related to computational complexity, and it is possible to use the reference RSSI data as center of our basis functions. For this reason, our RBF system has a unique solution and the design guarantees the exact fitting for all reference data.

The reference fingerprints and their corresponding coordinates (x_i, y_i) are employed to train the network and adjust the weights accordingly. Thus, given a RSS target p_j measured at location $z_j = (x_j, y_j)$, the output of the RBF network may be expressed as a weighted sum of normalized basis functions:

$$z(p_j) = \sum_{i=1}^{c} w_i \cdot \frac{\varphi(\| p_j - c_i \|)}{\sum_{k=1}^{c} \varphi(\| p_j - c_k \|)} \tag{6}$$

Where w_i are 2-dimensional weights. The parameter w_i may be determined to obtain a good approximation by optimizing the fit represented by Eq. (6), i.e. the difference between the RSSI values of the reference data and the RSS targets, to estimate the target coordinates given the known positions of the reference tags. Thus, we form the following set of equations:

$$z(p_k) = \sum_{i=1}^{c} w_i \cdot u(\| p_k - c_i \|), k = 1, ..., L \tag{7}$$

We calculate w_i by solving the system of linear equations based on Eq. (7) using the reference fingerprints in the database and their corresponding coordinates. Therefore, our resulting RBF avoids over-fitting. Subsequently, the weights w_i are used during localization to obtain a location estimate $\hat{z}$ given a new RSSI value p'_j according to:

$$\hat{z}(p'_j) = \sum_{i=1}^{c} w_i \cdot u(\| p'_j - c_i \|) \tag{8}$$

Every T seconds, it is evaluated whether there are new sensor data to estimate the target position using the RBF network. If there is updated information, the RBF is applied to perform the estimate of the target position, but if it is not the case (loss of signal, different sampling time of the RFID system), the particle filter is applied to estimate the next position based on the prior state of the target.

Therefore, for each RBF network implemented, a probabilistic algorithm is applied to estimate the next position of the target. As tracking technique we implement a *Particle Filter (PF)*, which is a powerful tool to construct a probability distribution over the target area representing the environment [28].

3.5. Path Estimation through Particle Filters

The particle filter is a probabilistic approach that uses recursive Bayesian filters based on Sequential Monte Carlo Sampling. The proposed technique computes a posterior distribution of the target's location using Sequential Monte-Carlo Sampling, which is capable of using an arbitrary a-priori distribution to compute a posterior distribution. This method is less computationally intensive than other probabilistic methods, as Kalman filters [28], avoiding any assumptions about intrinsic features of the process, and the uncertainty about the sensor data is dealt.

The algorithm followed starts with the particle set initialized uniformly. Then all particle positions are updated according to the motion model. In our case we consider a movement in the space (x, y) that follows a *random walk* model [29] to represent the human motion, which takes into account the error model in the obtained measures from the deployed RFID tags.

During the correction stage of the filter, particle weights are modified according to their distances to the real measurement, as Eq. (9) shows:

$$w(\vec{x}_t) = w(\vec{x}_{t-1}) \cdot \frac{p(\vec{y}_t \mid \vec{x}_t) \cdot p(\vec{x}_t \mid \vec{x}_{t-1})}{q(\vec{x}_t \mid \vec{x}_{t-1}, \vec{y}_t)} \tag{9}$$

Where $w(\vec{x}_t)$ represents the weights of the set of particles at instant t, $p(\vec{y}_t \mid \vec{x}_t)$ and $p(\vec{x}_t \mid \vec{x}_{t-1})$ denote, respectively, the probabilistic behaviour of the output model and the state model of the system, and $q(\vec{x}_t \mid \vec{x}_{t-1}, \vec{y}_t)$ is the approximation of the belief function.

It is important to note that the areas in which we want to solve the localization problem are defined by dividing the space into IR zones (according to the previously performed theoretical RFID signal distribution analysis), and several active RFID tags are deployed in each subarea. Therefore, the information inside each subarea is used to further estimate the user localization and carry out its tracking process. Thus, a RBF network and a Particle Filter are defined for each subarea, and the amount of data to process by each one depends on the number of reference tags deployed in each subarea, but in any case, the resulting RBFs and PFs are small enough, easy to train and offer good performances, satisfying the requirement of providing user location data in real-time. At the same time, statistical values of velocity are provided continuously, thanks to the particle filter, which will be able to be used later to determine the user activity level and adapt comfort services according to the users behavior.

Therefore, combining these two algorithms, a radial basis function network as an estimation technique and a particle filter as a tracking method, a good estimate of the motion of the monitored RFID tag is obtained, while an optimum number of sensors is required.

4. Experience Deploying and Testing the System

4.1. Deployment of the System

The reference building where our localization system has been evaluated is the Technology Transfer Center at University of Murcia [1], which was designed as a smart environment since its early stages of design.

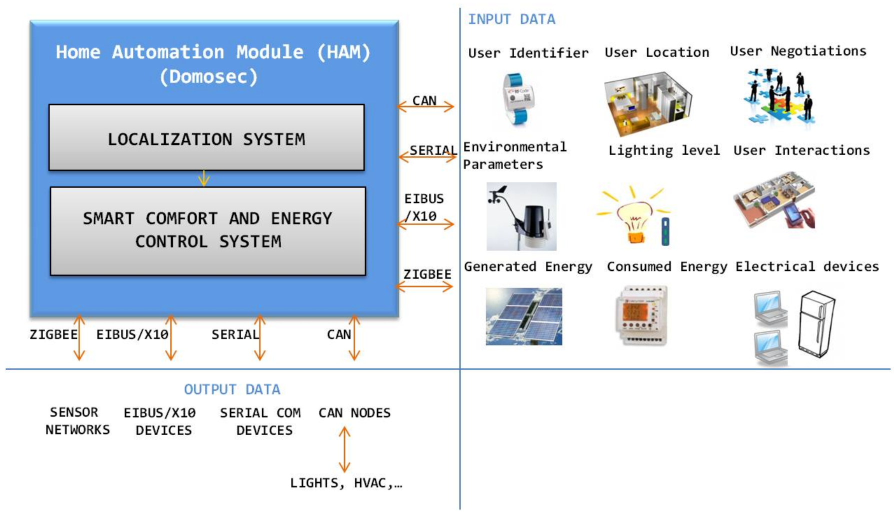

Figure 3: Distributed Data Collection Architecture

The hardware Architecture (Domosec) developed and deployed in this building (Figure 3) was troughly presented in [30]. The main components of this architecture are the network of Home Automation Modules (HAM) and the building gateway. All the environmental and location data measured by the deployed sensors are available in each of these modules. In Figure 3 we show all the inputs involved in our overall system, as well as the different type of connections with sensors and actuators.

[1] http://www.um.es/otri/?opc=cttfuentealamo

In this reference building, smart services are provided, such as the control and regulation of the lighting and HVAC appliances. In our work, different kinds of space belonging to a home environment have been simulated in a test lab of this building, such as a living room, a corridor, a bedroom, an office and a dining room. Each one of these locations with a different distribution of the HVAC and lighting appliances according to the features of the space (such as natural light, interior space activities and occupants' differences) and the estimated comfort requirements associated with them.

Figure 4 depicts the test lab of the Technology Transfer Center at University of Murcia where we have allocated different rooms/areas that represent a home environment and have carried out the essays described in the following subsection.

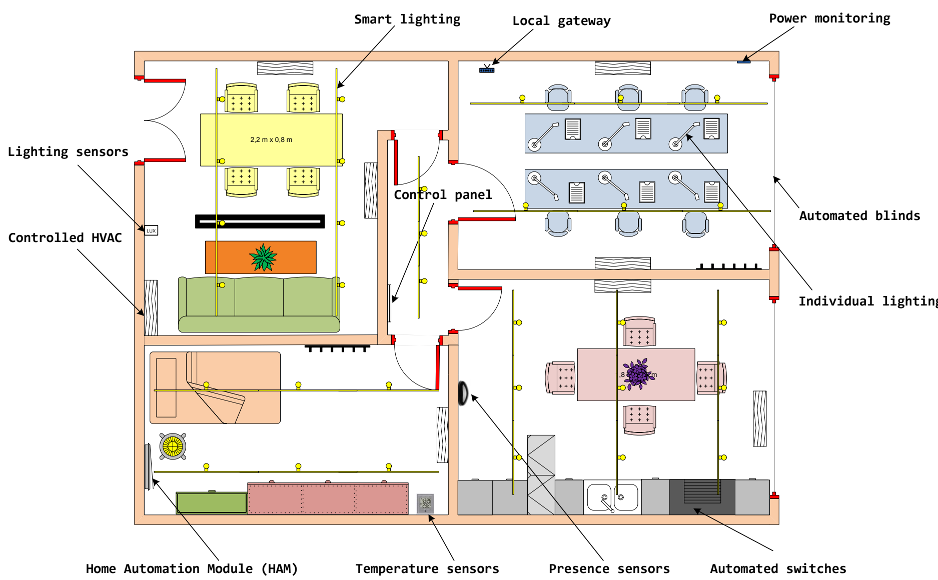

Figure 4: Distribution of space to simulate a home environment

Figure 5 shows a possible distribution of the different target location surfaces taking into account the distribution of lighting and HVAC appliances, as well as the user lighting and climate needs depending on the activities expected to be performed in each region (which are determined in accordance with the different work areas). Therefore, to satisfy the location requirements to provide customized services, our localization system must be able to locate a user within these different space surfaces.

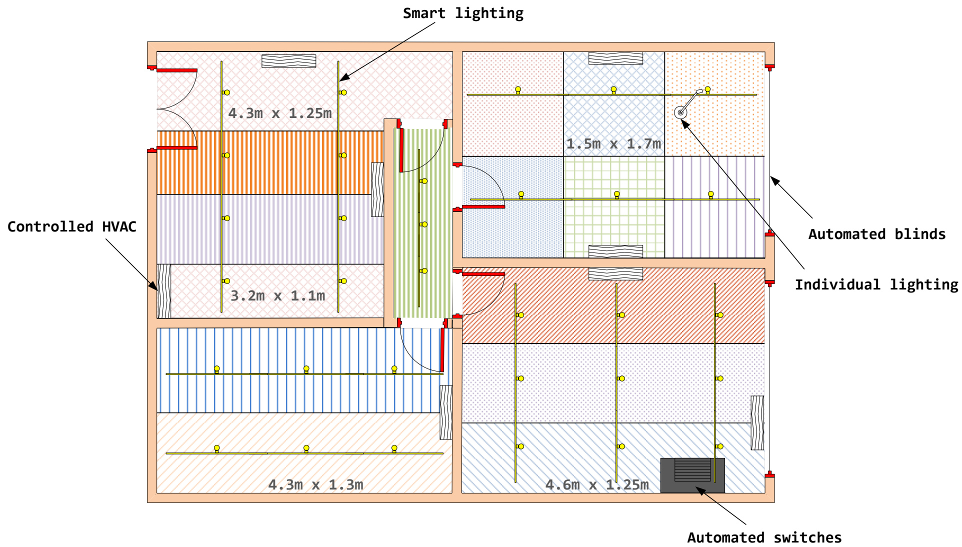

Figure 5: Target location surfaces according to the offered services

In this lab an RFID system is already available for access control, and various IR transmitters are already installed for the alarm system. Therefore, it does not require any additional equipment.

The RFID system used in our tests is based on IR-enabled RFID tags which initiates communication with the RFID reader, sending their data every 10 sec using the frequency band of 433 MHz. The transmission power of RFID tags is 28 μW, and the RFID reader has two radios, a channel with a maximum sensitivity of -58 dBm and another channel with -108 dBm, so that it is possible to configure various ranges of detection.

The RFID reference tags are placed in the ceiling of the test lab, and one IR transmitter is placed on the wall for every floor surface of $9m^2$ to optimize the total number of IR transmitters needed (according to the theoretical study of the RFID power distribution in this indoor environment [22]).

The distribution of reference tags is crucial to reach the accuracy requirements in the desired zones. For this reason, in the following subsections we analyze how it affects the accuracy of the location data obtained given different RFID reference tag distributions.

4.2. Experimental Tests

Firstly, it is important to bear in mind that the minimum accuracy achieved in the location data must be lower than the IR transmitter coverage. Consider that a single IR transmitter can be used to estimate the user location within a target area of $9m^2$.

In the previous work presented in [22], a distribution of tags in a grid of $1m$ x $1m$ was considered. Using this distribution, a 77% success in estimated positions with an error lower than $1.5m$ is reached. However, in practice it is not feasible to equip a whole building with tags placed at $1m$ of distance from each other, due to the consecuent cost, and the amount of data to process. Moreover, it is clear that an accuracy of $1,5m$ is not always needed to provide us with individual lighting and HVAC conditions.

The results obtained from the tests performed in our test lab are collected as statistical values of the error achieved in the estimated positions considering different RFID reference tag distributions. The tests performed represent different users behaviour and different conditions of context, such as very crowded space, few people, a lot of/few obstacles, a lot of/few human activities, etc. Table 1 shows the results corresponding to several days' monitored. As can be seen, they are quite accurate according to the location requirements of lighting and HVAC services, giving an acceptable error, even using a low number of reference tags.

Table 1: Statistical values of localization error for different distributions of the reference tags: me (mean error), mxe (max error) and mne (min error)

Location surface	**me (m.)**	**mxe (m.)**	**mne (m.)**
1m x 1m	1	2.6	0.3
1m x 1.5m	1.8	2.7	0.3
1m x 2m	1.2	2.9	0.3
1.5m x 1.5 m	1.3	2.7	0.4
2m x 2m	1.6	3.1	0.6
2m x 2.5m	1.9	3.3	0.6

In Table 2 we collect the successful cases related to the same previous distributions of reference tags, and given a maximum error in location estimation. These results allow us to analyze the general behavior of the proposed localization system.

As we can see, with a distribution of tags of $1m$ x $1m$ it is possible to obtain a 65% success rate in localization with an error less than $1m$, while a 98% of the cases have a maximum error distance less than 2.5m. These results ensure a good performance of our solution in terms of location error given the common target location surfaces to provide comfort services in buildings, such as those shown in Figure 5, where the worst case corresponds to solve localization within an area of 1.5m x 1.7m (to provide individual lighting in an office space), it means to have location data with a mean error lower than 1.5m. Therefore, with three of the five reference tag distributions analyzed in this work (1m x 1m, 1m x 2m and 1.5m x 1.5m), we can solve one of the most restrictive location problems in a home environment.

Table 2: Success rate in the localization mechanism given a mle (maximum location error)

Location surface	**mle<1m**	**mle<1.5m**	**mle<2m**	**mle<2.5m**
1m x 1m	65%	77%	96%	98%
1m x 1.5m	51%	73%	88%	92%
1m x 2m	45%	72%	81%	85%
1.5m x 1.5 m	42%	69%	75%	82%
2m x 2m	38%	64%	66%	78%
2m x 2.5m	37%	64%	65%	76%

In addition, contrasting with previous works that also use RFID systems for indoor localization, such as those collected in [23] (Landmarc, SA-Landmarc and SA-SVR), our work clearly reduces the final cost of the technological solution chosen, while the mean error in the location estimation is acceptable given our requirements in terms of accuracy in location data. Our investment in equipment is reduced due to the RFID reader is the most expensive device involved in these localization systems and in our purpose there is a single reader. Besides, the technology chosen to fuse with RFID data (and in this way providing stability to the localization mechanism), i.e. the IR technology, is a low-cost choice.

In Figure 6 an example of some tracking processes carried out in our test laboratory is showed using a distribution of reference tags of 1m x 1m and several IR transmitters. As can be noted, our localization system is able to monitor the users locations with a high accuracy according to the target location surfaces involved in the main comfort services provided in the different work areas.

On the other hand, for greater maximum errors than 1m in the location data provided, our system assures a good performance even when the surface

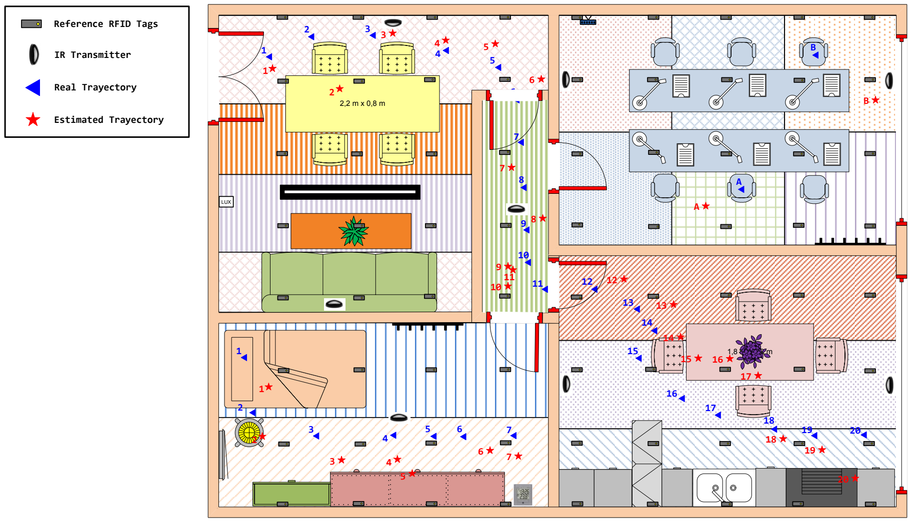

Figure 6: Tracking position using a distribution of reference tags of 1m x 1m

covered by reference tags is higher, being 62% the lowest value of successful cases in location for a location surface of $2m$ x $2.5m$ and with a mean error of $1.9m$. Furthermore, for location surfaces greater than $1.5m$ x $1.5m$, the success cases obtained with different maximum errors is similar. This shows a stabilization of the location error. Therefore, among these location surfaces, we can choose those requiring a lower number of reference tags, i.e. the distribution of $2m$ x $2.5m$ with a 64% of successful cases providing an error lower than $1.5m$, which is quite suitable considering the location requirements of our problem.

4.3. Analysis and Discussions

From the results of our tests, we can assert that using an IR transmitter per each $9m^2$ of location surface and a single RFID system with different distributions of reference tags, our localization mechanism ensures an adjustable location error, taking into account the location requirements of the pervasive services analyzed in this work.

The test lab where our essays have been performed is designed to provide flexibility in the distribution of space and appliances, using for this portables walls made of different material from the initial and fixed walls of the room. Therefore, these experimental results are also satisfactory in those cases in which the RFID signal shows a large variability, for instance, when to estimate the user location is needed to go through walls of different materials, i.e. with different coefficients of reflection, diffraction and absorption (as theoretically we had proved).

An important consideration to bear in mind is the best places to install the IR transmitters, since they need to have line of sight with the RFID tags. In the case of non line of sight with the monitored tags, despite the RBF can not be applied to estimate the positions, the PF is able to provide the users positions using previous information about their paths. However, the line of sight of the IR transmitters with the reference tags is an indispensable requirement in our localization system, since it affects directly in the accuracy achieved in the location data provided by our mechanism.

And finally, to choose the most appropriate distribution of reference tags, we recommend defining priorities among the different zones of a building regarding the duration and frequency of use. Thus, it may be possible to reach a tradeoff between the energy and hardware cost and the position accuracy. For example, in an office room where users stay for a long time daily, some accurate localization information is needed in order not to waste energy with inappropriate settings of comfort appliances. Instead, in a dining room where sporadic users appear, the energy wasted due to localization errors may be lower, because the poorly setup comfort appliance may be working during a short period of time.

Hence, after the evaluations performed, we can assert that this indoor localization system is both a cost effective and a realistic solution to provide positioning for services oriented to smart energy management.

5. Conclusions

In this paper a hybrid RFID/IR mechanism to solve the indoor localization problem is proposed. The localization solution proposed is focused on satisfying the accuracy location requirements needed to provide customized services in buildings, such as those involved in lighting and HVAC services.

Our mechanism is based on a regression method implemented using the RSSI values available in an RFID reader in order to estimate the location data of those users who wear an monitored RFID tag. Then, a particle filter is applied as a tracking technique to estimate the user path. This filter eliminates those estimated positions that do not fit according to a realistic movement pattern. This localization system is easily configurable, and totally embeddable in an automation platform.

Nevertheless, although this paper is based on a specific case study and on applying the localization mechanism proposed to smart buildings, it can also be applied in different scenarios where an RFID system and some IR transmitters are available, and where target users to be monitored only need to wear an RFID tag.

This system has been tested in real scenarios where a smart energy control wants to be performed depending on the presence and identification of users. The results obtained are satisfactoy, covering the accuracy requirements of localization data for pervasive indoor services. Therefore, we present it as both a cost effective and realistic solution for solving the indoor localization problem.

The current working line is defining predictive comfort models for indoor areas, considering the localization system proposed in this paper. In future studies we will test this indoor localization system taking into account different floors of a building, as well as in other types of buildings (for instance in a campus, a shopping mall, etc.) to verify its performance. In addition, considering location data about occupants, we will show details about the energy models and results obtained in terms of energy saved and comfort indexes achieved.

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