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Implementing a Real-Time Locating System Based on Wireless Sensor Networks and Artificial Neural Networks to Mitigate the Multipath Effect

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Abstract - Wireless Sensor Networks comprise an ideal technology to develop Real-Time Locating Systems (RTLSs) aimed at indoor environments, where existing global navigation satellite systems do not work correctly due to the blockage of the satellite signals. In this regard, one of the main challenges is to deal with the problems that arise from the effects of the propagation of radio frequency waves, such as multipath. This paper presents an innovative mathematical model for improving the accuracy of RTLSs, focusing on the mitigation of the mulipath effect by using Multi-Layer Perceptron Artificial Neural Networks. The model is used to implement a novel indoor Real-Time Locating System based on Wireless Sensor Networks.

Keywords: Wireless sensor networks, real-time locating systems, multipath effect, artificial neural networks.

1 Introduction

Whether in home automation, industrial applications or smart hospitals, *Wireless Sensor Networks* (WSNs) are used for collecting useful information for intelligent environments. In this sense, *Real-Time Locating Systems* (RTLSs) comprise one of the most interesting applications for WSNs. Among the most important factors in the locating process, we have the kinds of sensors used and the techniques applied for the calculation of the position based on the information recovered by these sensors. Outdoor locating is well-covered by systems such as the current GPS (Global Positioning System) or the future Galileo [1]. However, indoor locating needs still more development, especially with regard to accuracy and low-cost and efficient infrastructures [2] [3]. Therefore, it is necessary to develop Real-Time Locating Systems that allow performing efficient indoor locating in terms of precision and optimization of resources. In this regard, the use of optimized locating techniques allows obtaining more accurate locations using even fewer sensors and with less computational requirements [2].

Among the wireless technologies used to build indoor RTLSs, there are RFID (Radio Frequency IDentification), Wi-Fi (Wireless Fidelity), UWB (Ultra-Wide Band) and the low-power IEEE802.15.4/ZigBee standard [4]. Nevertheless, independently of the technology used, it is necessary to establish mathematical models that allow determining the position of a person or object based on the signals recovered by the sensors infrastructure. The position can be calculated by means of distinct locating techniques, such as *signpost*, *fingerprinting*, *triangulation*, *trilateration* or *multilateration*, among others [4] [5]. However, all of them must deal with important problems when trying to develop a precise locating system that uses WSNs in its infrastructure, especially for indoor environments.

There are different propagation effects that affect the transmission and reception of the electromagnetic waves throughout the wireless sensor infrastructures used by these systems. Among these effects there are *reflection*, *scattering*, *attenuation* and *diffraction* [6]. Thanks to the attenuation effect, it is possible to estimate the distance covered by a wave between a transmitter antenna and a receiver one [7]. This is very useful to build RTLSs based on these distances, as those based on trilateration [4]. However, reflection, diffraction and scattering effects lead to other problems such as *multipath*. This way, the expected distance covered by a wave is decreased or even increased due to the sum of waves reflected off the walls or the objects placed throughout the environment [7]. Specifically, both outdoor and indoor locating systems based on the measurement of distances between the sensors and the objects to be located can be affected by the *ground reflection effect* [6], a kind of multipath propagation effect.

In this sense, this paper proposes a novel indoor RTLS based on wireless sensor networks and a new mathematical model that uses *Artificial Neural Networks* (ANNs) as the main components to mitigate the ground reflection effect and calculate the position of the elements.

This paper is structured as follows. Section 2 explains the problems that the ground reflection effect introduces in indoor RTLSs based on wireless sensor networks. After that, Section 3 depicts a new proposal for reducing the ground reflection effect by using ANNs. Section 4 describes a novel indoor Real-Time Locating System based on wireless sensor networks where the new model has been applied to mitigate the ground reflection effect, Finally, Section 5 presents the conclusions obtained and depicts the related future work aimed at improving the proposed method.

2 Problem description

Real-Time Locating Systems based on Wireless Sensor Networks can be seriously affected by some effects related to the electromagnetic waves propagation, especially indoors [2]. Some of these effects are *reflection*, *scattering* or *attenuation*, among others. Such effects can provoke which is known as *multipath* effect, and, more specifically, the *ground reflection effect* [8].

2.1 Real-Time Locating Systems

The basic operation of a Real-Time Locating System is as follows. Firstly, it is necessary to deploy a network of reference nodes throughout the area or environment where locating will be carried out. Such nodes are usually called *readers* [4]. Some of these readers can move throughout the monitored area, acting as mobile references. In addition, there is a set of mobile nodes, known as *tags* [3] [4], which are carried by the users or assets to be located by the system. Each tag has a unique identifier that unequivocally identifies it in the system. Each of the tags sends a signal that contains its identifier in the system. This signal can be broadcasted periodically or as a response to other signals or excitations transmitted by the readers. In the latter case, the readers can be also called *exciters* [3]. The signals sent by the tags are detected by the readers within their coverage area. Thus, the readers can obtain the identifier of the tag that sends each signal and also gather some measurements of such a signal. These measurements give information about the power of the received signal (*e.g.*, RSSI or Received Signal Strength Indication), its quality (*e.g.*, LQI or Link Quality Indicator), its *Signal to Noise Ratio* (SNR) or the *Angle of Arrival* (AoA) to the reader, among many others. Finally, the information (*i.e.*, the reference measurements) from all of the readers in the network is compiled and processed to calculate the position of each tag. Nevertheless, there are RTLSs in which the position is calculated by each tag through different measurements from signals transmitted by distinct reference nodes and received at each tag (*e.g.*, GPS). However, in these kinds of RTLSs only each user knows its position, unless user devices transmit their own positions to another node through a certain data communication channel, such as GPRS or UMTS [1].

Real-Time Locating Systems can be categorized by the kind of its wireless sensor infrastructure and by the locating techniques used to calculate the position of the tags. This way, there is a combination of several wireless technologies, such as RFID, Wi-Fi, UWB and ZigBee, and also a wide range of locating techniques that can be used for determining the position of the tags. Among the most widely used locating techniques we have *signpost*, *fingerprinting*, *triangulation*, *trilateration* or *multilateration* [4] [5]. The set of the locating techniques that an RTLS integrates is known as the *locating engine* [4].

A widespread technology used in Real-Time Locating Systems is *Radio Frequency IDentification* (RFID) [3]. In this case, the RFID readers act as exciters transmitting continuously a radio frequency signal that is collected by the RFID tags, which in turn respond to the readers by sending their identification numbers. When a tag passes through the reading field of a reader, it is said that the tag *is* in that zone. Locating systems based on *Wireless Fidelity* (Wi-Fi) take advantage of Wi-Fi WLANs (Wireless Local Area Networks) working in the 2.4 and 5.8GHz ISM (Industrial, Scientific and Medical) bands to calculate the positions of the mobile devices (*i.e.*, tags) [9]. However, locating systems based on Wi-Fi present some problems such as the interferences with existing data transmissions and the high power consumption by the Wi-Fi tags. *Ultra-Wide Band* (UWB) is a technology which has been recently introduced for developing these kinds of systems. As it works at high frequencies (the band covers from 3.1GHz to 10.6 GHz in the USA) [10], it allows to achieve very accurate location estimations. However, at such frequencies the electromagnetic waves suffer a great attenuation by objects (*e.g.*, walls), so its use on indoor RTLS systems presents important problems. ZigBee is another interesting technology to build RTLSs. The ZigBee standard is specially intended to implement Wireless Sensor Networks and, as Wi-Fi and Bluetooth, works in the 2.4GHz ISM band, but can also work on the 868–915MHz band. Different locating techniques based on RSSI and LQI can be used on ZigBee WSNs (*e.g.*, signpost or trilateration). Moreover, ZigBee allows building networks of more than 65,000 nodes in a mesh topology [4].

Among the locating techniques that make up the locating engine we have the *signpost* technique, which determines the area on which each tag in the environment is located according to the closest reader to each tag [4]. On the contrary, *fingerprinting* is based on the previous study of some measurements of the electromagnetic waves in each zone of the monitored environment, thus estimating in which of such zones each tag is located [5]. On the one hand, *triangulation* calculates the position of each tag according to the angles of arrival of the broadcasted signals between tags and readers [4]. On the other hand, *trilateration* calculates the position of each tag from the estimated distance between each tag and a set of readers [1]. Finally, *multilateration* estimates the tags positions from the *Time Difference Of Arrival* (TDOA) of the received broadcasts from each tag to a set of readers [11].

The measurements used by these techniques include the received power of the signals (*i.e.*, RSSI), the quality of the received signals (*i.e.*, LQI) or the angle of incidence to the receiver antennas (*i.e.*, AoA). In an ideal environment, these measurements would be perfect, with no error or noise, and the calculation of tags positions would be exact. Nevertheless, in the real world, the electromagnetic waves are influenced by propagation effects such as *reflection*, *scattering*, *attenuation* and *diffraction*. These effects can make the readers to receive additional spurious signals that are undesired copies of the main signal, which makes up the *multipath effect*. When the ground is the main responsible of waves reflections, multipath can be modeled as the *ground reflection effect*.

2.2 The ground reflection effect

The detailed effects of phenomena as attenuation and reflection in the propagation of electromagnetic waves can be calculated by solving *Maxwell's equations* with some boundary conditions that model the physical characteristics of each object or medium involved [6]. As this calculation can be very complex or the physical characteristics of each object can be even unknown, there are some approximations to model signal propagation. One of these approximations is the *ray-tracing technique* that simplifies electromagnetic *wavefronts* to simple particles. Physically, each wavefront is the locus of spatial points presenting the same phase for a certain electromagnetic wave. In the ray-tracing technique, each wavefront is considered to be a particle traveling from the transmitter to the receiver antennas [6].

The propagation of electromagnetic waves between antennas is a well studied physical phenomenon. Let us consider that we have two antennas correctly aligned and polarized between them (whose gains are G_T for the transmitting antenna and G_R for the receiving antenna). Let us also suppose that such antennas are separated a certain d distance between them in the free space. Finally, let us consider that one of these antennas, the transmitter one, is transmitting an electromagnetic wave to the other antenna, the receiver one. When transmitting a monochromatic electromagnetic wave (or an enough narrow-band wave to assume a unique λ wavelength in the transmission medium) through the free space between two antennas correctly aligned and polarized, the received power is given by the *Friis transmission equation* [7]:

$$P_R = P_T G_T G_R \left(\frac{\lambda}{4\pi}\right)\left(\frac{1}{d}\right)^n \tag{1}$$

where P_R is the power available from the receiving antenna, P_T is the power supplied to the transmitting antenna, and n is the path loss exponent, that is experimentally calculated (*e.g.*, in the free space $n = 2.0$).

However, in the real life, an electromagnetic wave transmitted by a certain wireless source will be reflected, diffracted or scattered by the multiple objects placed throughout the environment. This way, the antenna of the destination node will receive undesired copies of the transmitted signal. Even worse, these additional signals will be possibly delayed in time and shifted in both frequency and phase. When a single ground reflection effect predominates in the multipath effect, a *two-ray model* can be used. In this model, it is considered that a radiofrequency signal is transmitted through the free space from a transmitter antenna to a receiver antenna. The distance of the bases of transmitter and receiver is d. It is supposed that the ground is a perfect infinite flat plain. Moreover, the height of the transmitter antenna over the ground is h_T, whereas the height of the receiver antenna over the ground is h_R. This way, the total energy of the signal in the receiver antenna is the sum of the energy of the directly transmitted wave between both antennas and the energy of one wave transmitted from the transmitter antenna and reflected off the ground. This reflected wave comes in contact with the ground with a θ_i incident angle and it is reflected with a θ_r reflection angle (by the *law of reflection*, $\theta_r = \theta_i$). Due to the difference of the phases of directly transmitted and reflected waves, they will be constructively or destructively added in the receiver antenna. As both the transmission medium (typically the air) and the ground can be considered as dielectric media, a portion of the incident wave on the ground is reflected by the junction between them and the rest of the energy passes through this junction. This way, considering both media as non-conductive and being the transmission medium the free space and the ground a dielectric whose relative permittivity is ε_r and relative permeability $\mu_r = 1$, the *Fresnel reflection coefficients* for horizontal and vertical polarized signals are given by:

$$\begin{cases} \Gamma_H = \dfrac{\sin\theta_i - \sqrt{\varepsilon_r - \cos^2\theta_i}}{\sin\theta_i + \sqrt{\varepsilon_r - \cos^2\theta_i}} \\ \Gamma_V = \dfrac{\varepsilon_r \sin\theta_i - \sqrt{\varepsilon_r - \cos^2\theta_i}}{\varepsilon_r \sin\theta_i + \sqrt{\varepsilon_r - \cos^2\theta_i}} \end{cases} \tag{2}$$

This way, Figure 1 shows how ground reflection effect influences the transmission range between a transmitter and a receiver in both the 2.4GHz (typical band used in Wi-Fi, Bluetooth and ZigBee) and the 868MHz (used by ZigBee in Europe) bands inside an office with soft partitions ($n = 2.6$, with a standard deviation $\sigma = 14.1$, and a permittivity $\varepsilon_r = 18$ for the ground), where transmitter and receiver are respectively sited at 2.5m and 1.1m height over the ground. These conditions are typical for indoor RTLS using WSNs. This figure shows how, due to ground reflection effect, the real received waves have more losses than ideally received waves. Even worse, the received power does not vary monotonically with distance. This means that, for certain local distances, we can have a higher received power even if the receiver is sited further away from transmitter and vice versa. Furthermore, if we want to guess the distance between a transmitter and a receiver from the received power, we can have more than one received power that could cause such a distance. As can be seen in the figure, the ground reflection effect is greater for higher frequencies.

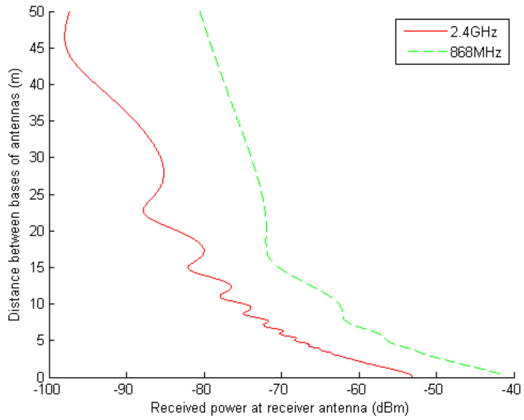

Fig. 1. Variation of the estimated distance regarding the received power at the receiver antenna using a two-ray model to consider the ground reflection effect.

2.3 Related approaches

There are some related approaches focused on the study or the mitigation of the multipath or the ground reflection effect. Xie *et al.* [12] present a multipath mitigation algorithm for a spread spectrum radio-frequency system using a frequency hopping technique and considering a two-ray environment. However, its integration with existing RTLSs is hard as it is based on the frequency hopping technique and implies to modify the wireless technologies used in the systems. Eui Seok Kim *et al.* [8] study the ranging performance through a two-ray multipath simulated model. This research uses IEEE 802.15.4a as wireless technology intended for indoor locating applications. Nevertheless, it is only a simulation with analysis proposals and does not propose a real way to mitigate the ground reflection effect. There are other approaches that use Artificial Neural Networks to performing locating techniques. Salcic and Chan [13] propose the use of an ANN to estimate mobile GSM phone positioning. This research includes the comparison of the ANN with a function approximation model. Nerguizian *et al.* [2] present a method for indoor mobile station location using received signal strength fingerprinting measurements applied to an ANN.

3 An innovative locating model

The innovative mathematical model proposed in this paper takes RSSI measurements as inputs and makes an estimation of the position of tags based on these RSSI measurements. RSSI has been selected because it is one of the most common measures used in current indoor RTLSs and it is also easy to obtain in most wireless technologies [4]. At a first stage, the model establishes the most probable distance of each tag based on the RSSI levels by mitigating the ground reflection effect. In the second stage, the generated data is used by the model to train an MLP (Multi-Layer Perceptron) neural network [14] which finally estimates the positions of each tag after the system has already been trained using standard location algorithms.

3.1 Mitigating the ground reflection effect

In ideal conditions, the modeling of the relationship between RSSI levels and distances between antennas has a decaying exponential shape. Nevertheless, as shown in Figure 1, when ground reflection effect is taken into account, the process of approximation of the relationship between the RSSI levels and the distances between antennas is complex and problematic. Therefore, it is necessary to use other models that allow considering the ground reflection effect in order to obtain a reliable estimation of the distances between tags and readers.

Currently there is a wide range of models for function approximation. Among the most widely used, we have the *regression models*. Regression models are based on the generation of mathematical functions that minimize a certain error function according to the training data. Usually, the error function utilized is the *least square error function*. There are different regression models regarding the existing relationship between the variables. This way, we have the *linear regression*, *exponential regression* or the *logarithmic regression models*, among many others. An alternative to these regression models is the *Support Vector Regression* (SVR) [15] [16]. The SVR method comes from a set of related methods which learn from data known as *Support Vector Machine* (SVM). SVM is a supervised learning technique that is applied to the classification and regression of different elements. SVM facilitates working with data that cannot be adjusted to linear models [15], initially conceived to obtain classifications in linear separable problems.

Other regression methods applied when the distribution of data and their relationships are unknown are *supervised learning neural networks*. These kinds of ANNs are applied in forecasting problems as, for instance, electric power consumption [17], gas consumption, or oil slick forecast [19]. In the work of Kalogirou [17] it is presented a complete review of case studies where these artificial neural networks have been applied. Among the supervised learning networks there are different alternatives for the learning process. This way, we have *error-correcting learning* [18], *delta rule* or *least squares learning* [18], *generalized rule* or *error backpropagation algorithm* (*generalized delta rule*) [18], *reinforcement learning*, or *stochastic learning*. Among supervised learning networks we have the *Multi-Layer Perceptron* (MLP) or the *radial basis function* (RBF) networks [20].

Artificial Neural Networks allow working with *time series*. The use of time series facilitates the forecast if it is not possible to make estimations of non-independent values with consecutive samples. This way, it is provided a more realistic forecast of values. Indeed, this is a fundamental feature for the forecast of distances from the RSSI levels, thus mitigating the ground reflection effect. This is because the ground reflection effect mainly occurs inside certain ranges of the distances.

As shown in Figure 1, the ground reflection effect registered in the signals varies regarding the RSSI level. As can be seen in such a figure, for a certain range of RSSI values, there are fluctuations in the distance values regarding the RSSI levels. Thus, a certain RSSI value can mean distinct distances. In order to model the ground reflection effect we utilize time series applied to Artificial Neural Networks. Specifically, we use a Multi-Layer Perceptron, as mentioned before. Artificial Neural Networks allow forecasting a value according to the received historical values. Therefore, in this work the neural network is provided as inputs both the current detected RSSI value and the RSSI values detected in previous time instants. This is the way we intend to mitigate the ground reflection effect. The neural network is made up of n input neurons, being n the time instants taken into account: $t, t - 1, ..., t - (n - 1)$. The intermediate layer of the neural network is configured following the Kolmogorov theorem [21] and choosing $2n + 1$ neurons.

In order to improve the forecast of the time series it was opted to incorporate the RSSI levels provided by other readers into the neural network. This way, the distances forecasting is done using a subset of the deployed readers in the system simultaneously. The architecture of the neural network is depicted in the Figure 2. This neural network has k input groups with n neurons each of them. These n neurons correspond with the n values of the time series. Likewise, the k groups correspond with the number of readers that are considered for the distance estimation. This number of readers is set in advance, thus selecting the readers with highest measured RSSI levels from the tag. The intermediate layer is made up of $2(k + n) + 1$ neurons, whereas output layer is formed by k neurons (*i.e.*, a neuron per each reader). The groups of input neurons are ordered according to the current RSSI level from highest to lowest. Therefore, the first output of the neurons is associated to the reader that received the highest RSSI level and so on.

3.2 Estimating the location of the tags

Our proposed model captures data from the estimation of the positions by the trilateration algorithm. It stores these in a memory to subsequently use to carry out the training of an MLP (Multi-Layer Perceptron). This way, the neural network allows us to make the fastest estimations and is more responsive to variations in the distances resulting from the reflections of the waves emitted. Input data in the neural network corresponds with the distances calculated by means of the MLP shown in Figure 2 from a pre-fixed number of readers and the position of the readers. These readers are selected according to the lowest distances they have to the tag. Output has two coordinates, one for each plane coordinate. The number of neurons in the hidden layer is $2n + 1$, where n is the number of neurons in the input layer. Finally, there is one neuron in the output layer. The activation function selected for the different layers has been the *sigmoid*. Furthermore, the neurons exiting from the hidden layer of the neural network contain sigmoidal neurons. Network training is carried out through the error backpropagation algorithm [14].

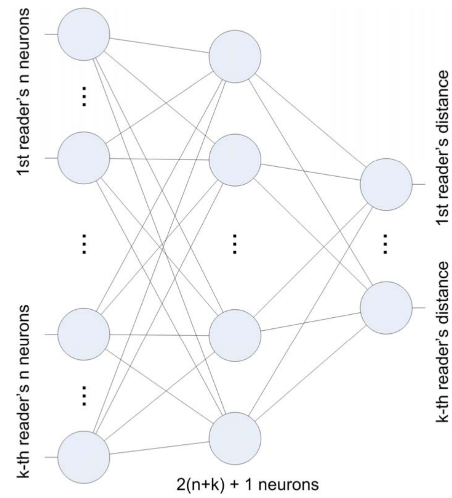

Fig. 2. Structure of the Multi-Layer Perceptron used in the training stage for the mitigation of the ground reflection effect using multiple readers. The ANN contains n inputs for each of the k readers and k outputs.

In the proposed model, the MLP used for estimating the tags positions has to be trained in each environment in order to get the highest accuracy in the locating process.

4 Implementing a new indoor RTLS

In order to test the performance of this model into an indoor environment, it has been developed and deployed n-Core Polaris, a new indoor RTLS based on ZigBee WSNs and the innovative locating technique proposed in this paper.

The basis WSN infrastructure of the system is made up of several ZigBee nodes (*i.e.*, readers and tags). As mentioned before, the ZigBee standard is specially intended to implement WSNs and allows operating in the frequency range belonging to the radio band known as *Industrial, Scientific and Medical* (ISM), specifically in the 868MHz band in Europe, the 915MHz in the USA and the 2.4GHz in almost all over the world. The underlying IEEE 802.15.4 standard is designed to work with low-power and limited computational resources. The ZigBee standard allows more than 65,000 nodes to be connected in a star, tree or mesh topology. These features make ZigBee and ideal supporting wireless technology for building indoor Real-Time Locating Systems. The possibility of working with low-power nodes that do not need large computational resources allows designers to reduce hardware costs when implementing the systems. In addition, these kinds of low-power nodes can reach battery life-time even of several years, regarding the transmission range (transmitted power), the time resolution and the accuracy of the system. ZigBee-based Real-Time Locating Systems can use different locating techniques in order to estimate the positions of the tags in the environment.

Fig. 3. n-Core Sirius B/D devices used by the n-Core Polaris RTLS.

In the proposed system, each ZigBee node includes an 8-bit RISC (Atmel ATmega 1281) microcontroller with 8KB of RAM, 4KB of EEPROM and 128KB of Flash memory and an IEEE 802.15.4/ZigBee transceiver (Atmel AT86RF230). These devices, called n-Core Sirius B and Sirius D are shown in Figure 3. They both have 2.4GHz and 868/915MHz versions and include a USB port to charge their battery or supply them with power [22]. Likewise, the USB port can be used to update the firmware of the devices and configure their parameters from a computer running a special application intended to it. On the one hand, n-Core Sirius B devices are intended to be used with an internal battery and include two general-purpose buttons. On the other hand, n-Core Sirius D devices are aimed at being used as fixed ZigBee routers using the mains power supply through a USB adaptor. In the n-Core Polaris RTLS, n-Core Sirius B devices are used as tags, while n-Core Sirius D devices are used as readers. This way, n-Core Sirius B devices are carried by users and objects to be located, whereas n-Core Sirius D devices are placed at ceilings and walls in order to detect the tags.

In Figure 4 it can be seen the basic architecture of the n-Core Polaris Real-Time Locating System. The kernel of the system is a computer that is connected to a ZigBee network formed by n-Core devices. That is, the computer is connected to an n-Core Sirius D device through its USB port. Such a device acts as coordinator of the ZigBee network. The computer runs a web server module that makes use of a set of dynamic libraries, known as n-Core API (Application Programming Interface). The API offers the functionalities of the ZigBee network. The web server module implements the innovative locating technique presented in this paper. This way, n-Core Polaris incorporates the described Multi-Layer Perceptrons in order to mitigate the ground reflection effect. On the one hand, the computer gathers the detection information sent by the n-Core Sirius D acting as readers to the coordinator node. One the other hand, the computer acts as a web server offering the location info to a wide range of possible client interfaces. In addition, the web server module can access to a remote database in order to obtain information about the users and register historical data, such as alerts and location tracking.

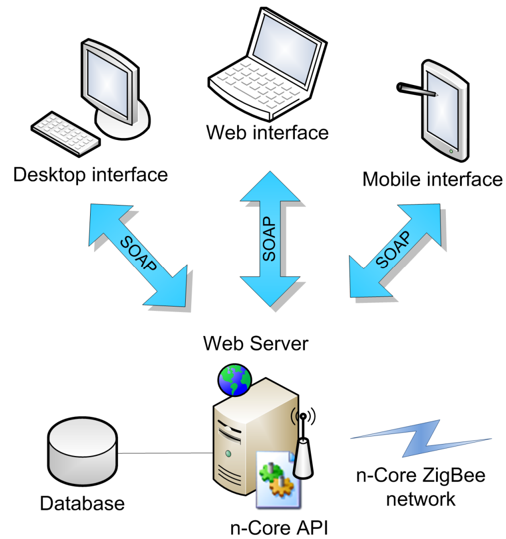

Fig. 4. Basic architecture of the n-Core Polaris RTLS.

The operation of the system is as follows. Each user or object to be located in the system carries an n-Core Sirius-B acting as tag. Each of these tags broadcasts periodically a data frame including, among other information, its unique identifier in the system. The rest of the time these devices are in a sleep mode, so that the power consumption is reduced. This way, battery lifetime can reach even several years, regarding the parameters of the system (broadcast period and transmission power). A set of n-Core Sirius D devices is used as readers throughout the environment, being placed on the ceiling and the walls. The broadcast frames sent by each tag are received by the readers that are close to them. This way, readers store in their memory a table with an entry per each detected tag. Each entry contains the identifier of the tag, as well as the RSSI (Received Signal Strength Indication) and the LQI (Link Quality Indicator) gathered from the broadcast frame reception. Periodically, each reader sends this table to the coordinator node connected to the computer. The coordinator forwards each table received from each reader to the computer through the USB port. Therefore, using all these detection information tables, the n-Core API applies a set of locating techniques, including that proposed in this paper, in order to estimate the position of each tag in the monitored environment.

Then, the web server module offers the location data to remote client interfaces as web services through HTTP (Hypertext Transfer Protocol) over SOAP (Simple Object Access Protocol). This way, the n-Core Polaris system includes three basic client interfaces: a desktop application, a web application and a mobile application. Figure 5 shows a screenshot of the web client interface. All these client interfaces has been designed to be simple, intuitive and easy-to-use. Through the different interfaces, administrator users can watch the position of all users and objects in the system in real-time. Furthermore, administrators can define restricted areas according to the users' permissions. This way, if some user enters in an area that is forbidden to it regarding its permissions, the system will generate an alert that is shown to the administrator or monitor user through the client interfaces. In addition, such alerts are registered into the database, so administrators can check anytime if any user violated its permissions. Likewise, administrators can query the database in order to obtain the location track of a certain user, obtaining statistical measurements about its mobility or the most frequent areas where it moves.

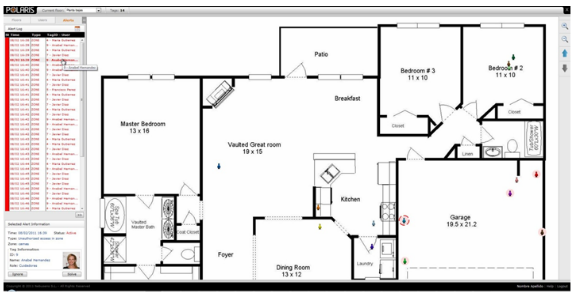

Fig. 5. Web client interface of the n-Core Polaris RTLS.

Furthermore, users can use one of the general-purpose buttons provided by the n-Core Sirius B devices in order to send an alert to the system. Similarly, administrators can send alerts from the system to a user or a set of users, which can confirm the reception using other of the buttons. The system not only provides locating features, but also scheduling and automation functionalities. The system can be integrated with sensor and actuator devices. These devices, called n-Core Sirius A, incorporate several communication ports (GPIO, ADC, I2C and UART through USB or DB-9 RS-232) to be connected to distinct devices, including almost every kind of sensor and actuator [22]. By means of the automation engine provided by the n-Core API, the n-Core Polaris system can schedule automation tasks, as well as monitor all sensors in the environment in real-time. All the information can be accessed through the distinct web client interfaces.

5 Conclusions and future work

Among the wide range of Wireless Sensor Networks applications, Real-Time Locating Systems are emerging as one of the most exciting research areas. Healthcare, surveillance or work safety applications are only some examples of the possible environments where RTLSs can be exploited. There are also different wireless technologies that can be used on these systems. The ZigBee standard offers interesting features over the rest of technologies, as it allows the use of large mesh networks of low-power devices and the integration with many other applications as it is an international standard working on unlicensed frequency bands.

The operation of Real-Time Locating Systems can be affected by undesired phenomena such as the multipath effect, and more specifically, the ground reflection effect. This paper proposes a new mathematical model aimed at improving the precision of RTLSs based on WSNs. The use of Artificial Neural Networks to forecast distances from RSSI levels allows improving the estimation of distances. In addition, focusing the forecast according to time series allows reducing the ground reflection effect that occurs when considering only the last RSSI measurement.

The use of measurements from several readers as inputs of the MLP in the proposed model also reduces the prediction error. This way, the ground reflection effect is mitigated and therefore the approximations provided by other methods with high adjustment goodness, as the logarithmic regression model were improved. This improvement in the distances forecasting is very relevant to estimate the positions of the tags, thus optimizing the overall calculations of locating techniques.

As future work it is planned the reduction of the number of readers necessary to perform the locating process, as well as the implementation in larger environments. Therefore, the system will subjected to an intensive set of experiments in order to validate both the mathematical model and the system. Details of these experiments and the results will be published in further complementary papers. Future work also includes the study of more detailed multipath models such as Ricean and Rayleigh fading or shadowing [23].

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