AN EVALUATION OF RSSI BASED INDOOR LOCALIZATION SYSTEMS IN WIRELESS SENSOR NETWORKS

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Abstract— This paper focuses on the analysis and comparison of existing indoor localization methods using wireless sensor networks (WSNs). The analysis lays emphasis on description of the most known localization techniques and investigation of their use in a WSN. Moreover, two RF-based location estimation methods using hyperbolic triangulation technique with RSSI information are proposed and compared to a third method using RF-based ambient mapping with artificial neural networks (ANNs). These methods are implemented and an experiment is conducted to investigate the advantages and drawbacks of each method.

Keywords— Localization, Location estimation, Wireless sensor networks, RSSI, ZigBee.

1 Introduction

The advances on mobile computing devices and the proliferation of local wireless networks have fostered the development of location-aware technologies and services. Physical location of various objects is one of the key piece of information in order to provide context-aware applications in an ubiquitous computing environment (Fukuju et al., 2003).

In outdoor environments, precise location information is easy to obtain through GPS (Global Positioning System) (Fukuju et al., 2003). However, in indoor environments the weakened GPS signal requires highly sensitive devices which substantially increases the cost of implementation. Thence, there have been several works focused on development of new indoor environment localization methods. Most recent research has emphasized on newer rapidly developing technologies, such as Wireless Local Area Networks (WLANs), Bluetooth and Wireless Sensor Networks (WSNs) (Giaglis et al., 2002). The localization scheme for these cases are mostly based on the radio propagation model and the relationship between the distance and RSSI (Received Signal Strength Indicator). The use of the RSSI is attractive because it requires no additional hardware, and is unlikely to significantly impact local power consumption, size and thus cost (Mao et al., 2007).

RADAR system, developed by Microsoft Research Group (Bahl and Padmanabhan, 2000), and the systems from Yin et al. (2005) and Nunes (2006) are RF-based localization systems that uses wireless LANs. The goal is to complement the data networking capabilities on RF wireless LANs with user location and tracking capabilities, thereby enhancing the value of such networks (Bahl and Padmanabhan, 2000). Nevertheless, this method requires costly and high energy consumption devices being advantageous only in net-works that already have these devices installed.

Thapa and Case (2003) investigates the Bluetooth adhoc network and its ability to be used for accurate and low cost indoor positioning by using Bluetooth signal strength information. Nonetheless, according to Dodd and Windsor (2006) and Monsignore (2007), the hierarchical nature of Bluetooth limits the size of a network to seven devices which makes its use impracticable in large WSNs.

Corral and Lima (2008), Ohta et al. (2005), Sugano et al. (2006), Alippi et al. (2005) and Terwilliger et al. (2004) present location estimation techniques using Wireless Sensor Networks (WSNs). WSN is a significant technology attracting considerable research interest (Mao et al., 2007). Nonetheless, WSN is associated to constraints in terms of cost and energy consumption. Therefore, most localization methods using WSNs are implemented in accordance to IEEE 802.15.4 ZigBee protocol, which is a low cost, low power consumption, reliable protocol for wireless control and sensing applications (Heile, 2005),(Dodd and Windsor, 2006).

Within this context, the purpose of this work is to develop localization systems using a wireless sensor network in an Ambient Intelligence environment. The Ambient Intelligence (AmI) is an emerging paradigm related to the development of human-centric "intelligent environment" that is characterized by embedded, context-aware, adaptive systems and technologies. This paper distinguishes from the previous in the sense that it presents and compares the most known indoor localization methods and investigates the effectiveness of two indoor localization systems, implemented in the same environment, using either hyperbolic triangulation method or artificial neural networks (ANN) ambient mapping.

This paper is organized as follows. Section 2 presents the most known methods for location es-

timation. In Section 3, a localization system based on RSSI measurements using hyperbolic triangulation is implemented and two techniques are employed to estimate the target's position. Also a location estimation system using artificial neural networks is implemented and analyzed. Experimental results are given followed by a comparative analysis of the implemented methods in Section 4. The conclusion is presented in Section 5.

2 Methods for location estimation

The majority of existing location estimation approaches consists of two basic phases: distance (or angle) estimation and distance (or angle) combining (Savvides et al., 2001). The main methods in order to estimate the distance (or angle) of the remote node are:

AoA (Angle of Arrival) - This method uses multiarray antennas with anisotropic radiation pattern in order to determine the incident radiowave signal direction of propagation. If a remote node transmitting a signal is in direct line of sight (LOS), then the multiarray antenna can determine from which direction the signal is coming from (Corral and Lima, 2008). The drawback of this method is the requirement of many antennas with anisotropic radiation pattern and, moreover, the previous knowledge of their pattern. Because of this particular demand and the costs involved with it, the AoA method is not recommended for most WSNs.

ToA (Time of Arrival) - This method is based on the measurement of the time of arrival of the signal transmitted by the remote node to different base stations (Corral and Lima, 2008). The propagation time can be directly translated into distance, based on the known signal propagation speed (Savvides et al., 2001). Furthermore, in order to calculate the distance between the nodes, two techniques can be employed. One can either measure the propagation time directly from one point to another or measure the roundtrip delay of the signal. Usually, the second approach is preferred because the first requires clock synchronization from the nodes. The ToA method is usually applied when the existence of ultrasound signals as in Fukuju et al. (2003), Harter et al. (1999) and Priyantha et al. (2001). Although, methods using ultrasound achieve high accuracy, each device adds to the size, cost, and energy requirements (Ohta et al., 2005). Therefore, the use of this technology does not usually go in accordance with the restrictions imposed by a WSN.

RSSI (Received Signal Strength Indication) - This method is based on the relationship between the power of the signal measured at the receiver in contrast to the known transmit power. Theoretical and empirical models are used to translate this signal attenuation into a distance esti-
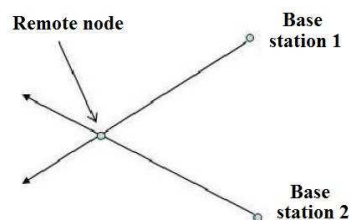

Figure 1: A triangulation system using the intersection of direct lines from two different base stations.
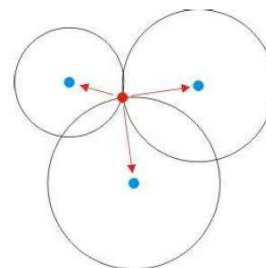

Figure 2: Location estimation based on the intersection of three hyperbolic asymptotes.

mate (Savvides et al., 2001). Although there are many sources of disturbances in this analysis, this technique is attractive for WSN since it requires no additional hardware, and is unlikely to significantly impact local power consumption, size and thus cost (Mao et al., 2007). Moreover, RSSI is presented in most wireless devices.

For the second phase, the most known methods for location estimation are:

Triangulation - This method is used when the direction of the remote node instead of the distance is estimated, as in AoA systems (Savvides et al., 2001). In order to estimate the position, at least, one second estimation coming from another base station is necessary (Corral and Lima, 2008). The position is estimated using trigonometry. The intersection of two or more estimated direction lines is used to estimate the position of the remote node. The intersection using two base stations is shown in figure 1 (adapted from Nunes (2006)).

Hyperbolic Triangulation - This method requires three or more sensor nodes to estimate the target's position. For each sensor, a hyperbolic asymptote is created using the measured distance between sensor and target. Then the position of the target is estimated by assessing the intersections of different asymptotes as shown in figure 2 (adapted from Dankwa (2004)). This method is usually used with ToA and RSSI technologies.

Nevertheless, in contrast with the previous methods Bahl and Padmanabhan (2000), Yin et al. (2005) and Alippi et al. (2005) present an ambient mapping solution for the location estimation problem. The method works by constructing

a signal strength behavior map (Mao et al., 2007). Usually, the map is constructed in an offline stage. The radio map is built by tabulating the signal strength values received from the base stations at selected locations in the area of interest (Yin et al., 2005). In the online localization phase, real-time RSSI measurements are used with the radio map to estimate the current location (Yin et al., 2005). Statistical or intelligent algorithms may be used to increase the effectiveness of this method.

In this paper, the hyperbolic triangulation method and the ambient mapping method using RSSI measurements are investigated. Both methods are implemented in the same workplace and a comparative analysis is performed based on the experimental results.

3 Localization system models

This section presents two location estimation systems using RSSI measurements from a WSN in an AmI environment. The WSN was composed by devices using XBee module from DIGI, which is an easy to implement, low cost ZigBee transceiver (Heile, 2005).

3.1 Hyperbolic triangulation

In this system, the hyperbolic triangulation method presented in section 2 is used to estimate target's position. The distance between each sensor and target is estimated based on a very popular radio propagation model that describes the relationship between signal strength and distance (Thapa and Case, 2003), the Inverse Square Law of Propagation (Hecht, 2002):

$$P = \frac{K}{D^2} \tag{1}$$

where P represents the power of the received signal at a distance D from the source and K is a constant that depends on environmental conditions.

Applying (1) with RSSI data is the starting point for any localization scheme based on radio signal strength (Dankwa, 2004). Nevertheless, since RSSI usually gives signal attenuation measurements instead of signal power, the model described in (1) may be written in terms of RSSI measurements as:

$$RSSI_{dBm} = 10log_{10}\left(\frac{K}{D^2}\right) \tag{2}$$

where $RSSI_{dBm}$ indicates the signal attenuation in mili-decibels for a source signal power of $1mW$.

The radio propagation model which is used in the proposed method is obtained taking the distance D from (2):

$$D = \sqrt{\frac{K}{10^{\left(\frac{RSSI_{dBm}}{10}\right)}}} \tag{3}$$
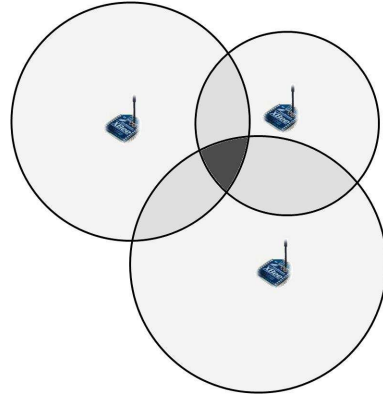

Figure 3: Overlap of the areas created by the hyperbolic asymptote of each sensor module.

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In real life scenarios, however, each environment presents a multitude of interference and multi-paths that make it more difficult to reliably predict the signal attenuation parameters and their distance correlation (Dankwa, 2004). According to MaxStream, Inc (2005), various distinguished factors can affect the intensity of the radio wave signal in a closed environment, such as the proximity of the RF-antenna to other objects, the antenna orientation, other wireless networks or systems, etc. Therefore, an empirical study was conducted offline in order to estimate the value of the constant K. Several RSSI data were collected at various distances and the least square method was used to adjust the parameter K so as to best fit the data set. Furthermore, since the localization method is based on analytical geometry, the ambient of implementation was discretized in small $1cm^2$ areas. The distance between each area and each sensor was calculated as:

$$d_{pi} = \sqrt{(x_{mi} - x_p)^2 + (y_{mi} - y_p)^2}$$

where d_{pi} is the calculated distance between the area p and the sensor i, x_{mi} and y_{mi} defines the known position (measured with a measuring tape) of the sensor i and x_p and y_p defines the center of the area p.

In the online stage, the localization algorithm estimates the distances between sensors and target using (3). Then, the algorithm covers all the discretized areas and calculates the mean square error of each area p (E_p) using the following equation:

$$E_p = \sum_{i=1}^{N} r_i - d_{pi} \tag{4}$$

where r_i is the estimated distance, using (3), between the sensor i and the target and N is the number of sensors.

Following (3) and (4) the algorithm estimates the location of the remote node using two different methods:
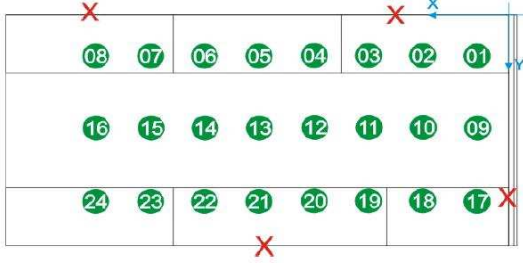
Figure 4: Reference positions of the remote node in the workplace.

Triangulation method (1) - This method follows (4) and estimates the location of the remote node using the area that exhibits the least error.

Triangulation method (2) - This method analyzes the area produced by the intersection of the hyperbolic asymptote areas from each sensor as shown in figure 3. The center of the intersection is considered to be the location of the remote node.

3.2 Ambient mapping using ANN

In this system, an artificial neural network location technique is used with a signal strength behavior map in the ambient of implementation. The radio map is built by measuring RSSI information at selected locations in the ambient. The resulting data is then used in neural network training with Feedforward-Backpropagation adaptive learning method.

The ANN is configured as follows: the RSSI data measured from each sensor is the input, while the estimated position x and y, from a cartesian geometry representation of the ambient, are obtained as outputs. Nonetheless, in order to simplify the ANN and to obtain better results, the ANN is divided in two different neural networks. The first is used to obtain the x position of the remote node while the second is used to obtain the y position.

For the training set, several RSSI data were collected at predefined positions and, for each, the mean RSSI value was calculated and used as the corresponding RSSI value for the position. From the data set, 80% is used for the adaptive training while the rest is used to investigate and validate the resulting ANN. Several ANNs are created using distinguished initial values, distinguished layers with different neurons and transfer functions and the one that best fits the data set is used in the online stage to estimate the location of the remote node.
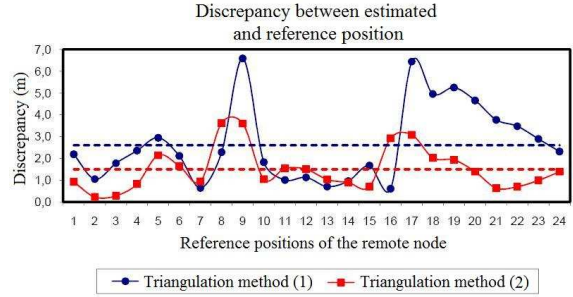

Figure 5: Discrepancy between reference and estimated position of the target using hyperbolic triangulation methods.
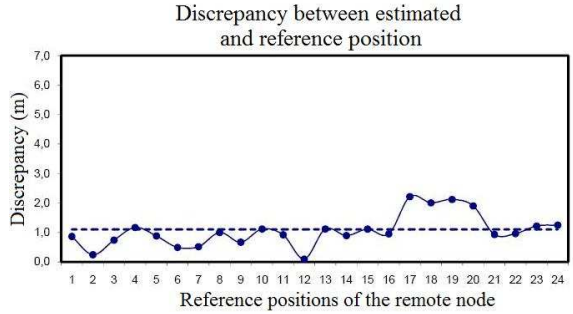

Figure 6: Discrepancy between reference and estimated position of the target using ambient mapping technique with ANN.

4 Experimental results

In this section, an experiment to investigate the location estimation systems described in Section 3 is presented. The experiment was conducted in a workplace (area: 7.5 m x 3 m) in the Laboratório de Automação, Visão e Sistemas Inteligentes - LAVSI, which is an AmI environment from the Department of Electrical Engineering of the University of Brasília (UnB). For the experiment, four sensor nodes equipped with XBee modules were used.

The experimental procedure was as follows. First, RSSI data was collected in different positions in order to estimate the best value for the constant K concerning the experimental environment using the least square method. Afterwards, the ANN training set was obtained by measuring RSSI information at 110 different predefined positions which resulted in a reason of 4.89 RSSI data per m^2.

In the online stage, the remote node was placed in 24 different locations in the room as shown in figure 4. For each location, RSSI measurements from sensors were used to estimate the target's location using the hyperbolic triangulation method (1) and (2) and using the ambient mapping with ANN technique.

The relationship between the predicted and actual location, obtained with a measuring tape,

of the remote node is presented in figures 5 and 6. The curves illustrate the discrepancy, mean squared error, between the estimated and expected value of target's location. This discrepancy may be used to describe the accuracy of each method. From figure 5, it is easy to observe that, for the given experimental conditions, the average position discrepancy was $2.60m$ for the triangulation method (1) and $1.50m$ for the triangulation method (2). Nevertheless, from figure 6, using the ambient mapping scheme, the average value of the position discrepancy was $1.05m$.

Therefore, one may conclude that the localization system using ambient mapping with ANN is more effective than the systems using hyperbolic triangulation methods. This is mainly because the ANN is trained in the experimental workplace and thus considers some of the unpredictable systematic environmental perturbations while training. Still, the performance of the ambient mapping with ANN is not so impressive because of the heavy influence caused by other non-systematic perturbations, such as the proximity to other objects and people.

5 Conclusions

In this paper, the problem of location estimation using wireless sensor networks in indoor environment was investigated. The work lays emphasis on analysis and comparison of the existing methods. Therefore, the most known localization methods are described and their use in a WSN is investigated.

Moreover, using the RSSI information collected by a set of sensors, two indoor localization systems are proposed and implemented applying either hyperbolic triangulation localization methods or offline ambient mapping method with artificial neural networks. Furthermore, the paper proposes two manners to estimate the target's position using the hyperbolic triangulation method.

An experiment conducted in an Ambient Intelligence environment with a ZigBee WSN indicates that the ambient mapping method is more effective than the first solution. This is mainly because of the unpredictable environmental perturbations, which deteriorates the accuracy of the distance estimation using the radio propagation model, that are taken into account during the ANN training. Nevertheless, this method requires the previous knowledge of the workplace which in many cases is a considerable restriction.

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