A Novel Approach to Indoor RSSI Localization by Automatic Calibration of the Wireless Propagation Model

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I. Extended Abstract

Context-aware systems unobtrusively assist people by predicting their needs. This prediction is often based on context information acquired from the environment. To this purpose we envision an assisted living supportive (*also called Ambient assisting living* AAL) scenario in which various embedded device (like sensors, actuators, display, and wireless medical devices) either operate independently or are coordinated under the local intelligence node. AAL is currently seen as the next evolution step in the information society. Thereby the computing science is being widened from stationary systems to ubiquitous, smart, and human-centric systems. In other words all systems are intelligent computer systems, which are not invasively embedded in the human environments, with the goal to improve the lifestyle based on the individual human needs. The first efforts to introduce context-awareness have been related to the localization of users [1], [2], [3], [4] and up to now localization is still one of the main building blocks of AAL architectures. The general solution based on Global Positioning System (GPS) is unfortunately available only in outdoor environments. In AAL scenario a viable solution to localization of users exploits wireless sensor networks. Sensor network-based solutions can estimate the (unknown) location of mobile sensors (placed on the users) with respect to a set of fixed sensor (called anchors), whose position is known, by using two different approaches, range-based or range-free localization schemes. The former is defined by protocols that use absolute point-to-point distance estimates for calculating location. The latter make no assumption about the availability or validity of such information.

The choice between these two localization approaches depend on the behaviour, requirements of protocols using location information, and on the wished error granularities. Acknowledging that the range-free solutions have a coarse accuracy, this technique in our AAL scenario, where the location precision is one of the main requirements, is inappropriate. Instead, a range-based localization solution may be appropriate in relation to the required location precision because it exploits measurements of physical quantities related to signals traveling between the mobile sensors and anchors. Radio signal measurements are typically the received signal strength indicator (RSSI), the angle of arrival (AOA), the time of arrival (TOA), and the time difference of arrival (TDOA). Recently, radio location based on a combination of AOA and TDOA techniques have been proposed, that guarantee a high-accuracy location but it requires a specific and complex hardware. In order to obtained a non-invasive system, our goal is to use health and patient sensors monitoring deployed in AAL scenario, and not a specific localization hardware like AOA and TOA techniques required. Because of RSSI does not require a special or a sophisticated hardware, but rather it has become a standard feature in most wireless devices, RSSI-based localization techniques are the best choice in AAL scenario. Moreover RSSI-based localization techniques do not have a significant impact on local power consumption, sensor size and thus cost. It is for these reasons that these techniques have received considerable research interest [5], [6], [7].

In [5] the authors suggest that algorithms that estimate distances between two wireless devices based on their reciprocal RSSI are unable to capture the myriad of effects on signal propagation in an indoor environment. Nevertheless, in [6] the authors have shown that despite the reputation of RSSI as a coarse method to estimate range, it can achieve an accuracy of about 2-3 meters RMS in a testbed experiment. Fading outliers can still impair the RSSI relative location system, implying the need for a robust estimator. A method to improve the quality of localization exploiting a number of RSSI measurements averaged in a time window to counteract interference and fading has been proposed in [7].

The main RSSI-based location approaches are based on *fingerprint* and on *signal propagation modeling* techniques. The fingerprint schemes also referred to as *pattern recognition* or *pattern matching* techniques, exploit the RSSI at the mobile sensors as a function of the mobile position during an off-line phase. Each mobile position is then identified by a set of RSSI. During the on-line phase the mobile location estimation is performed by matching the actual signature of the RSSI with the entries stored in a database available at the anchors. The database entries are usually collected on a grid of possible

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mobile positions within the area of interest, wherein the grid spacing must be always chosen as a tradeoff between performance and time required to fix the mobile location. The main drawback of this method is the extensive and accurate measurements, during the off-line phase, require to create the database. So, this procedure is very time expensive, as it requires human intervention, which is a practical barrier to its wider adoption.

The latter technique consists on developed a large-scale path loss model that accounts both free-space and loss due to obstructions in computing the RSSI in a given mobile position. As well as for the fingerprint technique also for this technique is required an off-line phase. During this phase also called *a priori calibration* the RSSI values are collected for a given mobile positions and used to develop a path loss model. In indoor environment such as AAL scenario the path loss model also take into account parameters such as the wall attenuation factor (WAF) and floor attenuation factors (FAF) to model the effect of walls and floors on the radio waves. Unfortunately, RSSI is environment dependent, moreover in indoor environments, the wireless channel is very noisy and the radio frequency signal can suffer from reflection, diffraction and multipath effect, which makes the signal strength a complex function of distance. To overcome these problems, wireless location systems use *a priori calibration* of the propagation model. The calibration works in two phases: the training phase and the estimation phase. In the training phase it is measured the RSSI at a grid of points in the area of interest, and in the estimation phase this information is used to estimate the propagation model parameters. Clearly, the accuracy of the calibration procedure depends on the number of points in the grid and to the number of measures taken per point. It is also clear that even this RSSI-based location approach need to human intervention and is time expensive.

In this paper we propose a novel localization algorithm that selects and weights the RSSI measures according to their strength, and it uses an automatic training that only exploits information from the anchors, without requiring human operators.

We assume a localization model comprising a set of *anchors* $A = \{a_1, a_2, \ldots, a_n\}$, a *mobile* and a *localization server* L. The anchors have well known position on the map, identified by the pair (x_i, y_i). Our localization model consists of two phases: the training phase and the localization phase. In the training phase each anchors transmit a broadcast beacon with theirs identifier to the other anchors, measuring the RSSI. These values are exploited by the localization server to estimate the propagation model parameters. In the localization phase each anchor periodically emits a beacon packet containing its identifier. The mobile node, which needs to be localized by the system, receives the beacons from the anchors, computes the corresponding Received Signal Strength Indicator (RSSI), and sends to the localization server the pair <RSSI, anchor id>. The localization server accumulates all the pairs and using the three anchors with a greater RSSI, estimates the distances between mobile and anchors exploiting a suitable propagation model. Using these distances as a radius of a circle, the algorithm estimates the intersection points between them. Given the set of the

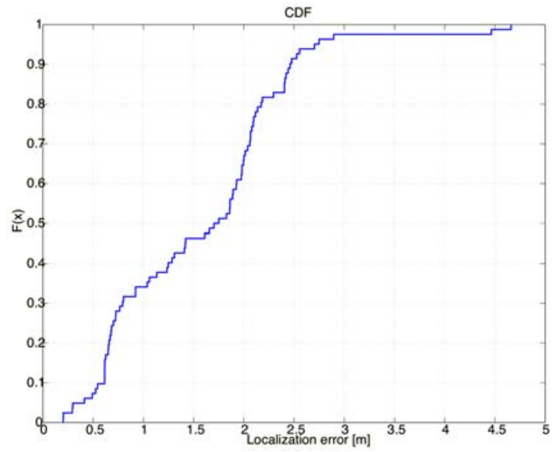

Fig. 1.Cumulative Distribution Function of the localization error.

intersection points, the location of a mobile node is calculated by choosing the three anchors with a greater RSSI, and by biasing the location estimate towards the “nearby” anchors.

Figure 1 shows the Cumulative Distribution Function obtained by using our localization algorithm in a testbed based on IEEE 802.15.4 devices. We obtained a better results with respect the RADAR [9], DALS [10] and the Bulusu [8] algorithm that obtains a 75th percentile location error under 5 m, the 87^{th} percentile location error of about 9 m, and the 90^{th} percentile location error within 3 m, respectively. Our localization performance are similar to that of MoteTrack system [11] that achieves a 50^{th} percentile and 80^{th} percentile location-tracking accuracy of 0.9 and 1.6 m respectively, but our algorithm does not require the expensive training phase of MoteTrack.

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