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RFID localization algorithms and applications—a review

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Abstract Object localization based on radio frequency identification (RFID) technology has promising potentials. By combining localization with its identification capability, existing applications can be enhanced and new applications can be developed for this technology. This paper starts with an overview introducing the available technologies for localization with a focus on radio frequency based technologies. The existing and potential applications of RFID localization in various industries are then summarized. Moreover, RFID localization algorithms are reviewed, which can be categorized into multilateration, Bayesian inference, nearest-neighbor, proximity, and kernel-based learning methods. Also, we present a localization case study using passive RFID technology, and it shows that objects can be successfully localized using either multilateration or Bayesian inference methods. The survey also discusses the challenges and future research on RFID localization.

Keywords RFID technology · Localization algorithm · Application · Multilateration · Bayesian inference

Introduction

One approach to ubiquitous computing is enabling applications and devices to detect and make use of changing environmental conditions. Such systems are also called context-aware systems, which have become an emerging topic in recent years. The goal of context-aware ubiquitous computing is to acquire and utilize information about the context of a device to provide services that are appropriate to the particular people, place, time, and events (Moran and Dourish 2001). Location, one kind of situational information, plays an important role in many context-awareness applications, such as monitoring parts and inventory in a manufacturing facility, tracking the product flow in the distribution chain, guiding tourists in a museum, and many others.

Radio frequency identification (RFID) is an automatic identification (auto-ID) technology that relies on remotely storing and retrieving data using tags and readers. The wide adoption of this technology by industries in recent years has been brought by the following two main driving forces. First, the manufacturing processes for passive RFID tags have been much simplified and automated, and thus the production cost has been dramatically decreased. Manufacturers have started to offer sub 10-cent UHF tags in 2007, earlier than the predicted year 2008 (O'Connor 2005a). Second, the mandates from government agencies and major retailers have forced suppliers to quickly adopt this technology in an unprecedented way. Other factors, such as the attractive encryption capability and low energy consumption, also contribute to the adoption of RFID technology. One also should note that the adoption rate of RFID technology is in fact slower than the expectations and forecasts, due to the high investment on infrastructure, and the lack of RFID standard (US Department of Commerce 2005; Matta and Moberg 2006). The tracking applications of RFID technology have been reported in industries, including manufacturing industry (Baudin and Rao 2005; Ranky 2006), food industry (Angeles 2005), transportation and logistics (Eckfeldt 2005; Lu et al. 2006), and agriculture industry (Fishkin et al. 2005).

Besides the general existence or non-existence information within the range of RFID detection, the accurate location information of the objects is desired for many applications. This is particularly true when multiple RFID tags are detected

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and it is required to differentiate one item from another before the operations can be performed on the right one. Other existing technologies, such as global positioning system (GPS) technology, are not feasible in many occasions, in particular, when indoor environments are involved or the relative high cost of GPS devices is a prohibiting factor. RFID technology itself becomes a possible solution to obtain object location information since the RF signal strength between a reader and a tag reflects the spatial information between them. Obviously, object localization based on RFID technology is a convenient and valuable addition to the applications where item tagging is already required. The purpose of this paper is to provide a comprehensive survey on the applications and algorithms of this emerging technique. The paper is organized as follows. In section "Overview of localization techniques", we present an overview of the existing localization techniques. In section "Applications of RFID localization", current and potential applications of RFID localization are introduced. In section "RFID localization algorithms", we summarize the existing algorithms for RFID localization. In section "Localization case study based on passive RFID technology", we show a localization case study using passive RFID devices. Finally, related research challenges are discussed and further research is called for in the last section.

Overview of localization techniques

A variety of methods have been developed for the purpose of object localization. They can be classified into RF-based techniques and non RF-based techniques. The non RF-based localization techniques include audio-visual localization, ultrasonic localization, infrared localization, and laser localization. Meanwhile, RF-based localization techniques include GPS technology, wireless local area network (WLAN) localization, and RFID localization. The pervasive nature of RF signals provides these techniques certain advantages over the non RF-based ones.

Non RF-based localization

Audio, vision, ultrasound, infrared and laser techniques have been widely applied to object localization for a long time. Typically, localization is realized based on time-of-arrival of signals and the multilateration algorithm. The bat location system (Addlesee et al. 2001) is a good example. A pulse of ultrasound is emitted from a transmitter attached to the target object, and the signal is received by receivers. The distance from the transmitter to each receiver can be calculated based on the time-of-flight and the speed of sound in air. The 3D position of the object can be determined by the multilateration algorithm if three or more such distances are given. Object orientation information can also be obtained by finding the relative positions of two or more Bats attached to the object. Other examples include the localization of high-speed mobile robots based on laser light source (Lingemanna et al. 2005), and the localization of badges in a building based on the infrared communication between badges and sensors in the building (Want 1992). In general, these localization techniques are relatively mature, but they are vulnerable to environment disruptions. For instance, audio systems are sensitive to noises, and vision and laser systems can be easily blocked by the obstacles in their application space.

GPS

Global positioning system (GPS), developed by the United States, is a localization technology based on a constellation of about 24 satellites orbiting the earth at altitudes of approximately 11,000 miles. Similar systems are being developed by other countries. As the most widely used localization system, GPS employs time-of-arrival of RF signals for localization. It measures the time delay between transmission and reception of each GPS radio signal to calculate the distance to each satellite, and applies the principle of multilateration to determine the position.

GPS have been used in resources investigation, transportation navigation and monitoring, electronic mapping, and military operations. A GPS system mainly consists of GPS satellite constellation, ground control network, and user equipment (often called GPS receivers). There are two levels of service, namely, a standard positioning service (SPS) for general civil use; and a precise positioning service (PPS) for military use which demands higher position accuracy. While GPS works well outdoors, it performs poorly or even can not work in indoor environments. This is because the radio signals are blocked by buildings, and thus the transient time-of-light is rather difficult and costly to measure (Manpure et al. 2004).

WLAN localization

This technique uses WLAN devices as localization sensors and beacons, and localizes the object according to the signal strength information between the object and the beacons. Compared with the non RF-based localization sensors, such as cameras and laser range-finders, WLAN localization has several advantages. First, the devices are inexpensive and light-weight, and have low power consumption. Second, an increasing number of environments are pre-equipped with suitable beacons in the form of WLAN access points, which provides a convenient infrastructure for localization. Nevertheless, WLAN devices are usually required to wire with a computer or a controller, and this makes WLAN localization systems not very portable and only good for indoors environments.

Numerous studies on localization using WLAN devices can be found in literature, and we only cite a few instances here. Smaliagic and Kogan (2002) developed a localization system using IEEE 802.11b wireless network by using the multilateration algorithm, as well as a quadratic polynomial representing the distance-signal strength relation. Similarly, Castro et al. (2001) developed a wireless localization device that uses Bayesian networks to infer the location of objects covered by IEEE 802.11 wireless network. Ladd et al. (2002) conducted a series of localization experiments with a laptop and a PCMCIA wireless Ethernet card. The localization precision of less than 1 m with a probability of 0.64 was achieved. Howard et al. (2003) studied the use of WLAN as a localization sensor for mobile robots. It shows that given a sufficient number of beacons and a signal strength map, robots can be localized to a resolution of 0.5 m. Yu et al. (2006) investigated the performance of different position estimation methods by using the time-of-arrival of ultra wideband signals. The low cost/low complexity system was successfully tested in a ski field where skiers were tracked and localized.

RFID localization

RFID localization is similar to WLAN localization in principle. It typically employs the RF signal strength, instead of time-of-arrival of signal, as an indicator of distance. Its main advantage over the WLAN technique is the easiness of deployment—RFID tags are portable and do not require cables for communication. Due to the nature of RF signals, the algorithms developed for WLAN localization are also suitable for RFID localization, which are to be discussed in details in section "RFID localization algorithms".

Active RFID tags, powered by on-board batteries, often have an effective read range of more than 100 m. This gives them a clear advantage over passive tags, whose read ranges are significantly shorter. Also, localization using passive RFID devices is generally more challenging because the communication between the tag and the reader is more sensitive to environment settings such as the tagged materials and the orientation between the tag and the reader antenna. Therefore, most of the RFID localization research has been on active RFID devices to date. However, passive RFID localization is attractive because the cost of a passive tag is only an insignificant fraction of an active tag. Frequency determines the core characteristics of RFID systems. Among the passive tags of different frequencies, LF and HF tags are generally less effective for localization in that their typical read ranges are less than 2 m, while UHF and microwave tags are preferred due to their longer read ranges (up to 6 m). On the other hand, for many instances, HF tags could be chosen over UHF tags because they have greater tolerance of water. For the purpose of localization, research is needed to boost the read range of passive RFID systems. Existing studies on RFID localization will be summarized in the following sections.

An extension of WLAN and RFID localizations is the localization based on wireless sensor network (WSN), which consists of a number of sensor nodes (devices) with transceivers. The basic function of a sensor node is "sense and send"—the data will be collected, passed through the network, and sent to a server computer for processing. Similar to RFID tags, the sensor nodes do not need wired connection, and thus WSN localization can be easily deployed in many applications (Bulusu et al. 2000; He et al. 2004; Arora et al. 2004). As compared with the centralized communication structure of RFID technology, the distributed topologies of wireless sensor networks, namely, the intercommunication capability between nodes, can significantly increase the detection range.

Applications of RFID localization

Container positioning system

The port of Singapore manages the arrivals and departures of more than 50 ships and monitors thousands of multi-ton cargo containers daily. Directing each container to its destination is critical, or serious consequences may take place, such as delayed departures or incomplete shipments. The positioning of containers has been achieved by using RFID technology with a centralized electronic data interchange (EDI) system. The backbone of the system originates from the installation of thousands of RFID transponders into the asphalt road of the port shipyard to create a multi-dimensional grid. The containers on the port shipyard can be accurately located based on the coordinates of the reference RFID transponders and the unique codes on the tags.

Application in healthcare

Localization of patients, staff, supplies and equipment is very important for healthcare centers to improve service, save costs, and reduce risks. Pilot projects in hospitals demonstrate that RFID localization is a valuable approach. LANDMARC, an RFID localization system (Li et al. 2004), has been applied to facilitate the management of hospitals and other organizations in case of emergency. The system operates at the frequency of 308 MHz, and is composed of active tags, landmark tags, readers, and communication devices. The position of an active tag can be determined by comparing the signal strength detected and the signal strengths of landmark tags. Using this system to monitor the infectious patients can reduce the number of healthcare professionals and ensure timely response for emergency. Meanwhile, integrated business systems and services (IBSS) announced a success pilot study for using RFID technology to locate assets and personnel at a large healthcare facility in Chicago (O'Connor 2005b). Emory Healthcare successfully deployed 2.45 GHz active RFID devices to track infusion pumps and other high-value equipment to improve asset management and utilization (O'Connor 2007). Note that the last two healthcare applications do not employ localization algorithms, instead, they estimate the object location based on the detection from a nearby sensor. The accuracy of location can be improved by integrating localization algorithms.

Application in construction material management

Tracking the location of construction resources enables effortless progress monitoring and supports real-time sensing of construction status. Jaselskis and El-Misalami (2003) developed a prototype RFID tracking system for improving the material procurement process on a construction site. Furthermore, Song et al. (2007) developed a method to locate materials on construction sites. The method requires a field supervisor be equipped with an RFID reader and a GPS receiver. The GPS receiver provides the absolute position information of the supervisor, while the position of the material relative to the supervisor can be determined from the multiple communications between the reader and the tag attached to the materials.

Local positioning system for road safety

Intelligent vehicles initiative was announced by US department of transportation (DOT) in 1998 to improve the road safety with a focus on the vehicle intelligence of collision avoidance. Tong and Zekavat (2007) developed an RFID-based positioning system, called wireless local positioning system (WLPS), for such purpose. The system operates at 3 GHz, and consists of two major components—a dynamic base station on a mobile and a number of transceivers with unique identification numbers in mobile targets. Periodic ID request signals are sent out from the dynamic base station, and the transceivers respond if they are in the coverage area. The transceivers' location is determined by the dynamic base station based on the algorithms of the time-of-arrival and direction-of-arrival estimations.

Production process control

With the constant shrinking of product life cycle, more and more companies adopt mass customization strategy in order to stay competitive. RFID localization can be helpful on this aspect. To handle the large number of production processes and frequent rearrangements of the machinery and other technical equipment, Infineon Technologies applied active RFID localization to facilitate its flexible, operator-centric automation system (Thiesse et al. 2006). The system uses UHF RFID tags with integrated ultrasonic sensors for fine-grained localization. Ultrasound emitters on the ceiling periodically send signals that are received by active RFID transponders. The tags calculate the time-of-flight for all received signals and store these values in their read/write memory. RFID controllers read the data from the tags and transfer them to a central server that calculates location information for all objects in the system.

AGV routing

Automatic guided vehicles (AGVs) are widely being used in plants and warehouses to transport loads of material to places that might otherwise be serviced by fork lift trucks, conveyor, or manual cart transports. They are the preferred choices when medium-high volume of repetitive movement of material with little human involvement is required. Traditional AGVs are guided by the paths predefined by embedded conductive wires or paint stripes. Updating or rearranging plant layout, in this case, will be challenging because the AGV paths have little flexibility to be adjusted. Autonomous AGVs overcome this drawback by discarding the fixed paths. Instead, the decision on routing is made possible from real-time location detection using the sensors on the AGVs and distributed in the host environment. RFID technology is a promising technique for guiding autonomous AGVs. It is believed that the localization and collision avoidance system on AGVs will be simplified if RFID devices are equipped. The experiments conducted by Azenha and Carvalho (2007) show that RFID localization can be used to guide AGVs, and overall it performs better than ultrasonic and laser techniques in terms of positioning accuracy.

Inventory management

Inventory consists of a substantial portion of operation cost for manufacturers and retailers. Many companies have automated the inventory management processes to better meet customer demand and reduce costs. However, how to efficiently obtain accurate inventory remains as a challenge. For instance, the investigation (Kang and Gershwin 2005) shows that the overall inventory accuracy of a global retailer is only 51%. Inventory inaccuracy mainly results from misplaced items. It is shown that on average, 16% of the items in the stores of a leading retailer in the United States are not placed in the correct places (Raman et al. 2001). The tracking capability of barcode and RFID technologies are useful on this aspect. However, the localization of items by RFID technology can further reduce the chance of misplacement, and also can help the operators to find the misplaced items in the event of such incidents. The study by Hariharan (2006) demonstrates that localization can significantly reduce the time to retrieve the misplaced items in a warehouse.

Application in mining safety

Collisions between haulage equipment and pedestrian workers or vehicles incur serious safety problems in mining industry. Various technologies, such as radar, video and ultrasonic, are known to prevent the collisions, but they have certain inherent limitations (Ruff and Hession-Kunz 2001). Malmberget mine in Sweden installed a mining safety system in 2003 to improve the safety of their workers. The system makes use of several "access points" installed at strategic locations in the mine. All workers are equipped with UHF active RFID tags, which are recognized and registered when they are within the reading range of the access points. The system stores and displays the number and the last location of personnel, so that the rescue team can quickly locate them under emergency. Similarly, several RFID localization systems have been tested or applied in coal mines in China (Zhang and Yuan 2006). These systems can monitor the variation of environments underground, and guide the workers to security places should a danger occur.

RFID localization algorithms

It seems that the biggest challenge for RFID localization is how to mathematically model the variation of the RF signals in space. Theoretically, a propagation model can be applied to calculate the distance according to signal strength or time-of -arrival. In unobstructed free space, Friis transmission equation (Friis 1946) shows that the signal strength level decreases at a rate inversely proportional to the distance travelled,

$$P_r = P_t \frac{G_t G_r \lambda^2}{16 L \pi^2 d^2}, \tag{1}$$

where P_r is the power received by receiver antenna, P_t is the power input to transmitter antenna, G_t is transmitter antenna gain, G_r is receiver antenna gain, L is system loss factor, λ is wavelength, and d is the distance between transmitter antenna and receiver antenna. Based on this relationship, we can estimate the distance between the RFID tag and the reader if the received signal strength is known. In real world applications, this model becomes less useful because phenomena such as fading, absorption and blocking reduce the signal strength; reflection and refraction result in multi-paths of propagation; multi-source signal may interfere with each other and collide at the receiver. For this reason, other methods such as statistical analysis are developed to calibrate the relationship between signal strength and distance. Another general

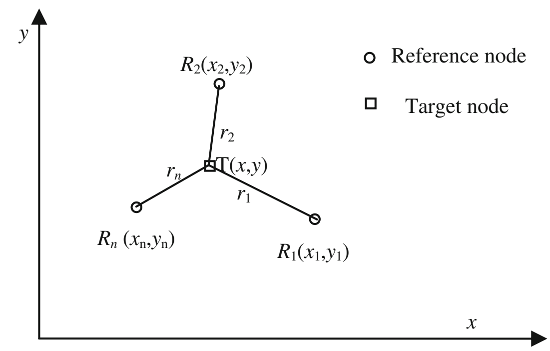

Fig. 1 Schematic of multilateration method

approach is to directly localize objects without relying on signal propagation or calibration. As such, RFID localization algorithms can be classified into two groups. Algorithms in the first group employ two-step approaches, namely, the calibration of the RF signal distribution in a specific environment, and then the estimation of object position. Multilateration and Bayesian inference algorithms belong to this group. Algorithms in the other group bypass the first step and directly compute the object position information based on signal strength data. Examples are nearest neighbor, proximity, and kernel-based learning algorithms.

Multilateration

Multilateration estimates the coordinates of the target node from the distances between the target node and the reference nodes with known coordinates. Figure 1 shows the schematic of 2-D localization using multilateration, and it can be easily extended to 3-D space.

If there are n reference nodes R_k, $k = 1, 2, \ldots, n$ with known coordinates (x_k, y_k), and the distances between the target node, T, with unknown coordinates (x, y) and reference nodes are estimated to be r_k, $k = 1, 2, \ldots, n$ we can obtain

$$\begin{cases} r_1^2 = (x - x_1)^2 + (y - y_1)^2 \\ r_2^2 = (x - x_2)^2 + (y - y_2)^2 \\ \qquad \cdots \\ r_n^2 = (x - x_n)^2 + (y - y_n)^2 \end{cases}. \tag{2}$$

By subtracting each of the other equations from the first equation and denoting $b_{i1} = \frac{1}{2}(x_1^2 - x_i^2 + y_1^2 - y_i^2 + r_i^2 - r_1^2)$, $i = 2, 3, \ldots, n$ we linearize this system of equations as

$$\begin{cases} (x_1 - x_2)x + (y_1 - y_2)y = b_{21} \\ (x_1 - x_3)x + (y_1 - y_3)y = b_{31} \\ \qquad \cdots \\ (x_1 - x_n)x + (y_1 - y_n)y = b_{n1} \end{cases}. \tag{3}$$

System (3) can be written in the matrix form:

$$AX = b, \tag{4}$$

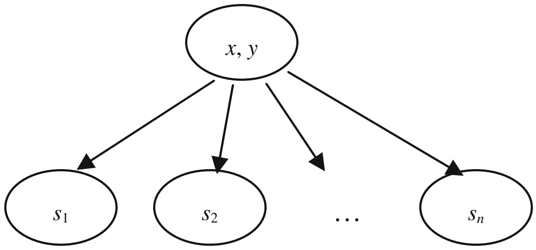

Fig. 2 Bayesian network for stationary localization

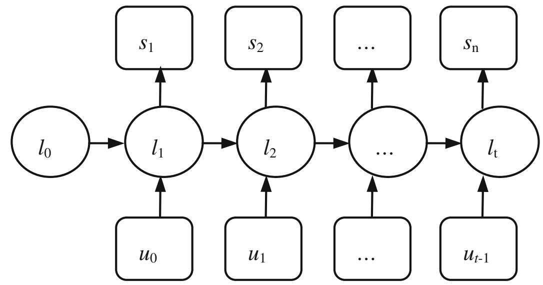

Fig. 3 Bayesian network for localization of mobile targets

where

$$A = \begin{pmatrix} x_1 - x_2 & y_1 - y_2 \\ x_1 - x_3 & y_1 - y_3 \\ \cdots & \cdots \\ x_1 - x_n & y_1 - y_n \end{pmatrix}, X = \begin{pmatrix} x \\ y \end{pmatrix}, b = \begin{pmatrix} b_{21} \\ b_{31} \\ \cdots \\ b_{n1} \end{pmatrix}.$$

When the estimated distances, r_k, have no errors, the formulation with three reference points can produce a unique solution. With the consideration of errors, more reference points should be used to improve the accuracy of localization. As a result, (4) becomes an overdetermined system. To obtain the coordinates of the target node, we can transfer (4) to a linear least squares problem:

$$\text{Min} \, \|AX - b\|^2 . \tag{5}$$

Normal equations, QR-factorization, and singular-value decomposition (Reichenbach et al. 2006) are the typical methods to solve (5). Multilateration is a mature algorithm, which is easy to code and requires less computation effort. As such, it is being widely used in many localization studies (Smaliagic and Kogan 2002; Savarese et al. 2002; Payne et al. 2006; Moore et al. 2004; Medidi et al. 2006) as well as pilot or commercial localization products (Hightower et al. 2002).

Bayesian inference

Bayesian inference is a statistical inference in which evidence or observations are used to update or infer the probability that a hypothesis may be true. The basic principle for localizing a stationary target by Bayesian inference can be represented by Fig. 2, where (x, y) are the coordinates of the target node, and S_i, $i = 1, \ldots, n$ are a series of signal strength transmitted to or received from one or more reference nodes by the target node. Generally, for 2-D localization, we assume that given (x, y), the probabilities of s_i are independent of each other, and thus, the system satisfies Markov condition.

According to Bayesian Rule, the position of the target node can be obtained by the following recursive equation,

$$\begin{aligned} P((x, y)|s_1, s_2, \ldots, s_n) &= \alpha P(s_n|(x, y)) \\ &\quad \times P((x, y)|s_1, s_2, \ldots, s_{n-1}), \end{aligned} \tag{6}$$

where α is a normalizing factor to ensure the sum of posterior probability $P((x, y)|s_1, s_2, \ldots, s_n)$ to be one, and $P(s_n|(x, y))$ calculates the probability of signal strength given the location of the target node. One of the unique advantages of Bayesian inference is that it can update the belief of the target's location from the dynamical data of signal strength. This property makes this method effective in localizing mobile targets, such as the AGVs in manufacturing facilities. Under the Markov assumption, the general Bayesian method to localize a mobile target can be expressed,

$$\begin{aligned} P(l_t|s_{1:t}, u_{0:t-1}) &= \alpha P(s_t|l_t) \int_{l_{t-1}} P(l_t|l_{t-1}, u_{t-1}) \\ &\quad \times P(l_{t-1}|s_{1:t-1}, u_{0:t-2}) dl_{t-1}, \end{aligned} \tag{7}$$

where $P(l_t|s_{1:t}, u_{1:t-1})$ is the probability that the target node is at location l_t given a series of observations $s_{1:t}$ (e.g. RF signal strength), and a series of movements $u_{1:t-1}$; $P(s_t|l_t)$ is the observation model; $P(l_t|l_{t-1}, u_{t-1})$ is the motion model, which predicts the probability of the current location l_t given the previous location l_{t-1} and the movement u_{t-1}; and α is a normalizing factor. If l_t is calculated at a set of discrete points, the integral in (7) is replaced with a summation over the entire set.

Model (7) can be represented by Fig. 3, where l_0 is the initial location of the mobile target. Using this model, the location of the mobile target is dynamically updated in an iterative way. Depending on the application environment, Kalman filters (Klee et al. 2006; Chen et al. 2007), multi-hypothesis tracking(Jensfelt and Kristensen 1999; Reuter 2000), grid-based approaches (Burgard et al. 1996, 1997), topological approaches (Blaer and Allen 2002; Kwon et al. 2006), and particle filters (Schulz et al. 2003; Howard 2006; Xu et al. 2007) are general techniques to represent the density function, $P(l_t|s_{1:t}, u_{0:t-1})$, and then to estimate the location by model (7). In brief, Kalman filters assume Gaussian distribution for the predictive probability and the initial state. This technique is robust and computationally efficient only when the assumption is valid. Grid-based approaches can deal with any non-Gaussian distributions, but have the drawback in computational load. Particle filters represent uncertainty by random sampling instead of probability density function, and

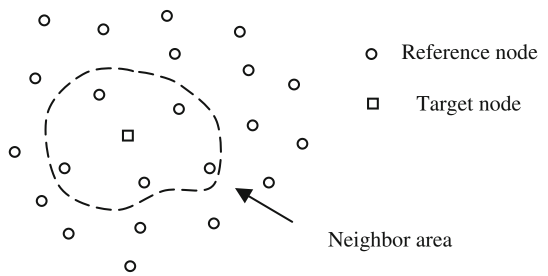

Fig. 4 Schematic of nearest-neighbor method

thus they combine the accuracy of grid-based localization with the efficiency of Kalman filters.

Nearest-neighbor

The idea of nearest-neighbor method is rather intuitive—the closer two points, the smaller the difference between the signal strengths of the two points, and thus an object can be localized by its neighbors. As shown in Fig. 4, the coordinates of the target point, (x, y), can be obtained by (8),

$$\begin{cases} x = \sum_{i=1}^{k} w_i x_i \\ y = \sum_{i=1}^{k} w_i y_i \end{cases}, \tag{8}$$

where (x_i, y_i), and w_i, $i = 1, 2, \ldots, k$, are the coordinates and weights of the reference points in the neighbor area, respectively; and k is the number of nearest neighbors. w_i are computed from the difference of the RF signal strengths on the target node and the reference points. They can be obtained by either (9) or (10),

$$w_i = \frac{1/\sum_{j=1}^{m} |s_{ij} - s_j|}{\sum_{i=1}^{k}\left(1/\sum_{j=1}^{m} |s_{ij} - s_j|\right)}, \tag{9}$$

$$w_i = \frac{1/\sqrt{\sum_{j=1}^{m} (s_{ij} - s_j)^2}}{\sum_{i=1}^{k}\left(1/\sqrt{\sum_{j=1}^{m} (s_{ij} - s_j)^2}\right)}, \tag{10}$$

where s_j and s_{ij}, $j = 1, 2, \ldots, m$, are the signal strengths at the localized point and the ith reference point respectively by the jth anchor device communicating with the target and reference nodes; and m is the number of anchor devices. This method avoids the signal propagation estimation, and it is suitable for the complex non-isotropic environments and it is not sensitive to the variation of application environments (Krishnan et al. 2004; Adult et al. 2005; Lorincz and Welsh 2007). This method has been successfully used for localization in some applications such as health care systems (Thiesse et al. 2006).

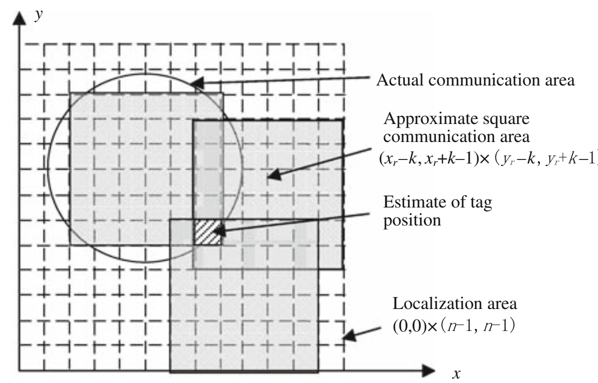

Fig. 5 Schematic of proximity method

Proximity

As shown in Fig. 5, proximity method uses the approximate communication area to detect whether the target node is in a region or not. The method requires less computation than Bayesian inference, but its positioning accuracy is usually poorer. Without loss of generality, we suppose an RFID tag is to be localized by a mobile reader. The localization area is partitioned into $n \times n$ congruent square cells with the side length of one unit, with each cell located at the coordinates $(i, j)\ 0 \le i, j \le n-1$. The communication area of the reader can be approximated by a square composed of $2k \times 2k$ cells. If the reader detects the tag at m known positions, (x_r, y_r), $r = 1, \ldots, m$, at each position the communication area is a union of cells $(x_r - k, x_r + k - 1) \times (y_r - k, y_r + k - 1)$. The intersection of these communication areas is

$$\begin{aligned}&(\underset{r}{Max}(x_r - k, 0), \underset{r}{Min}(x_r + k - 1, n - 1))\\ &\quad\times(\underset{r}{Max}(y_r - k, 0), \underset{r}{Min}(y_r + k - 1, n - 1)).\end{aligned} \tag{11}$$

The location of the tag can then be estimated by computing the centroid of this intersection area.

Simic and Sastry (2001) applied proximity in a random ad hoc communication network, and constructed a bounding model for algorithm complexity by computing the expected value of the position estimate and the perfect estimate. Based on this algorithm, Song et al. (2007) developed a proximity localization method to locate materials on construction sites. Similarly, He et al. (2005) proposed a proximity-based method for localization in wireless sensor network. A target node with unknown position is determined to be or not to be in a number of triangular areas, each of which is formed by three anchor nodes within the reading range of the target node. The centroid of the intersection of these triangular areas reveals the location of the target node.

Kernel-based learning

Kernel-based learning (KL) methods localize objects based on the fact that the smaller the distance between two nodes in signal space is, the closer they are in the physical space. Instead of transforming signal strength to physical distance by a propagation model, KL methods work directly with the signal strength. They can be divided into two categories. One is classification, which estimates if the location is in a defined area. When the target is classified into multiple overlapped areas, the location of the target can be estimated from the centroid of the intersection (Li et al. 2002; Nguyen et al. 2005; Brunato and Battiti 2005). This is similar to proximity method, but it uses a more general form because the overlapped areas can take arbitrary shapes. The other is regression, which directly estimates the value (Pan and Yang 2007; Pan et al. 2005, 2006; Brunato and Battiti 2005), or the probability distribution (Ferris et al. 2006, 2007) of the coordinates of the target.

A KL method learns its parameters from a sample of training data, $(x_i, y_i), i = 1, 2, \ldots, n$, where $x_i = (x_{i1}, \ldots, x_{im})$ is a vector of radio signal readings transmitted from m access points and received at the ith training point, and y_i is a measurement of the physical location. The measurement is a binary variable when a classification algorithm is applied. If the location of the training point is classified as inside a defined physical region, $y_i = 1$; otherwise, $y_i = -1$. When a regression algorithm is used, the measurement is the coordinates of the training point. Given the training data sample, a KL method can be generalized into the following three phases.

Phase I—defining the kernel matrix

A kernel matrix $K = (k(x_i, x_j)), 1 \leq i, j \leq n$ is composed of the kernel functions, $k(x_i, x_j)$, each of which measures the similarity between two data points, x_i and x_j, in the signal space. Typically, two types of kernel functions are used (Nguyen et al. 2005). One is the Polynomial kernels,

$$k(x_i, x_j) = \left(\left\|x_i - x_j\right\| + c\right)^d, \tag{12}$$

where c and d are parameters to be determined in real applications, and $d < 0$. The other is Gaussian kernels,

$$k(x_i, x_j) = \exp\left(-\frac{\left\|x_i - x_j\right\|^2}{\sigma^2}\right), \tag{13}$$

where σ is a parameter to be determined.

Phase II—learning the discriminant function

A discriminant function is defined as,

$$f(x) = \sum_{i=1}^{n} \alpha_i k(x_i, x), \tag{14}$$

where x_i are the training data, and x is the vector of signal readings obtained by the object, whose location is to be estimated. α_i are the parameters to be determined, which are learned from the training data. To learn the parameters, the function with unknown parameters is applied to estimate the location of each entry in the training sample with known location.

Phase III—online localization

Online localization phase estimates the location of unknown nodes, by putting the vector of signal readings x into the discriminant function obtained in the previous phase. The function, $f(x)$, gives the estimated location. Similar to y_i in the training data, the function value can be binary for a classification algorithm, or be the value or probability distribution of coordinates for a regression algorithm.

Other related techniques

Calibration-reducing techniques

For the two-step algorithms, signal calibration is indispensable for obtaining a propagation model. This process is usually time-consuming, so calibration-reducing techniques are needed to improve the efficiency of localization. Savvides et al. (2001) estimated the positions of as many unknown nodes as possible in a fully distributed fashion of wireless network, for reducing the calibration effort of training, and thus making the localizing system more robust to environment variance. Chai and Yang (2007) analyzed how to reduce the calibration effort in wireless localization by using unlabeled samples from the traces of the moving object. Unlabeled samples have no location information and are easier to obtain than calibration data. Interpolation was employed to estimate the unlabeled locations by labeled locations, based on the linear assumption of the signal strength. Pan and Yang (2007) used Graph Laplacian to recover the locations of both the access points and mobile devices by using radio signal strengths from the labeled and unlabeled positions. The method differs from others in that it treats mobile devices and access points in a completely symmetric manner.

False-read reduction

There are two types of false reading in RFID localization: if the reader detects a tag which should not be read, a false positive reading occurs; if it fails to detect a tag in the reading range, a false negative reading occurs. Either type impairs the performance of RFID localization. Brusey et al. (2003) developed two techniques to reduce false positive and negative reads during the localization process of RFID tags. To address false negative reads, a top-hat function was defined to exclude all reads taking place in a designated time-length, Δt, before the current time, t_{now}.

$$f_{hat}(t) = \begin{cases} 1 & |t_{now} - t| < \Delta t \\ 0 & otherwise \end{cases}. \tag{15}$$

Then a Gaussian weighting function was used to calculate a weighted average based on the age of the tag reading. To mitigate the effects of missing and unreliable readings, Jeffery et al. (2006) developed a framework of sensor data cleaning infrastructures for pervasive applications. It employs declarative cleaning mechanisms based on temporal and spatial characteristics of sensor data.

Localization case study based on passive RFID technology

The low cost of passive RFID tags presents a unique opportunity for object localization, but the related studies are scarce. For this purpose, we carried out a feasibility study on localization of passive RFID tags. It focuses on the 2D localization, in which the RFID reader and tags are kept on the same plane. For simplicity, stationary objects, instead of mobiles, were localized using both multilateration and Bayesian inference algorithms.

In the experiment, the hardware devices, as shown in Fig. 6, include an Alien 9780 RFID reader, Alien AL-9610 circular antennas, and a number of Alien Gen1 Squiggle RFID tags (915 MHz). Both the antennas and tags were mounted on wood frame structures of the same height. The support frame structure for antennas was attached to a rotating table to study the effect of tag orientation. The experiments were carried out in an open field to avoid the interference of the RF noise. Because the RFID reader can not output signal strength, we had to use readcount as an indicator of signal strength. Readcount is defined as the number of successful read among a certain number of reading attempts in each interrogation cycle from the reader. As a result, a larger readcount indicates a stronger signal strength, and vice versa. In our experiments, the reading attempts in an interrogation cycle were set to 100. Two localization algorithms, namely, multilateration and Bayesian inference methods, were applied to calculate the object position.

Fig. 6 Alien 915 MHz RFID systems for localization experiment

For multilateration method, we calibrated the distribution of the RF signal by measuring the readcounts at different distances and orientation angles between the antenna and tags. By taking both the distance and the orientation angle into account, five empirical propagation models were constructed at the different orientation angles,

$$c = \begin{cases} 94.36 + 19.05d - 9.60d^2 & 0^\circ \\ 91.31 + 19.28d - 10.04d^2 & 15^\circ \\ 96.12 + 13.81d - 11.17d^2 & 30^\circ \\ 93.59 + 27.20d - 24.00d^2 & 45^\circ \\ 90.24 + 47.47d - 60.20d^2 & 60^\circ \end{cases}, \tag{16}$$

where c and d represent the readcount and the distance (in meter) respectively, and orientation angle is the angle between the antenna surface and the tag surface. To localize objects, multiple antennas were used to collect the readcounts of RFID tags randomly placed in a rectangular area of 1.83 m × 1.83 m (6 ft × 6 ft). The calibration models in (16) were applied to estimate the distances between the antennas and the tags based on the readcounts obtained. Equation 5 was then solved to obtain the coordinates of object.

As for Bayesian inference method, the probability distribution of readcount was constructed at the intervals of 0.15 m and 15°. For each measuring point, we collected 1,000 readcounts. Then the probability of each level of readcount was estimated by its relative frequency. Table 1 shows the probability distribution of the readcount of the tag at the position of 1.83 m (6 ft) and at the angle of 0° with respect to the antenna surface. The probability distributions at other positions and orientations have the same data structure. The probabilities were then fed into (6) as $P(s_i|(x, y))$ to iteratively compute the posterior probability, $P((x, y)|s_1, s_2, \ldots, s_i)$. We developed a computer code to use both algorithms to compute the object positions. Figure 7 shows a screenshot of the Bayesian inference module of the code. One hundred random points were localized for both algorithms, and

Table 1 Probability distribution of readcount at one position

Distance (m)	Orientation angle (°)	Readcount	Probability
1.83	0	88	0.004
1.83	0	89	0.006
1.83	0	90	0.013
1.83	0	91	0.025
1.83	0	92	0.043
1.83	0	93	0.078
1.83	0	94	0.099
1.83	0	95	0.128
1.83	0	96	0.135
1.83	0	97	0.132
1.83	0	98	0.125
1.83	0	99	0.098
1.83	0	100	0.077

interrogation cycle was repeated for 100 times at each point. As a result, we obtained 10,000 entries of localization result for each algorithm. Naturally, localization error is the distance between the estimated position and the true position. Two statistics for the localization results were calculated. One is the mean of the localization error, which represents the accuracy of the localization algorithm. The other is the standard deviation of the localization error, which represents the precision of the localization algorithm. For multilateration method, the mean and standard deviation of localization error are 0.19 and 0.24 m, respectively. For Bayesian inference method, the values are 0.37 and 0.11 m, respectively for. In this preliminary test, Bayesian inference performs not as well in terms of the accuracy but excels the multilateration method in terms of repeatability.

Conclusive remarks

RFID technology appears to be a viable method for object localization. The combination of the localization capability and the identification capability provides unique advantages for this technology in many applications. In this study, we introduce the existing localization techniques, present a broad picture of the applications of RFID localization, and summarize the localization algorithms reported in literature. The survey provides a comprehensive overview about the state-of-the-art of RFID localization. In addition, due to the importance of passive RFID technology and little existing research on passive RFID localization, we perform an experimental study to localize passive RFID tags by using two algorithms—multilateration and Bayesian inference. The results show that localization of passive RFID tags is feasible by either algorithm.

Compared with other localization techniques, RFID localization is still in its early stage of development. Although it has exciting potentials, there are challenges that need to be solved so that the robustness and performance can be further improved. The following issues represent some of the major challenges and consequently research is called for.

1. RF signals in indoor environments usually exhibit multipath propagation due to the environment effect from obstructing structures such as walls and corridors. This causes large variations among the reads and complicates the modeling of signal propagation, and affects the performance of the localization algorithms relying on signal propagation. Research on modeling environment effects is very limited (Bahl and Padmanabham 2000; Madigan et al. 2005), and more robust models need to be developed.
2. In general, localization algorithms assume that the environment characteristics do not change with time. However, phenomena such as the moving of operators and vehicles and the running of a machine in many occasions could lead to an unstable environment. This affects the collection of signal data, and distorts the relationship

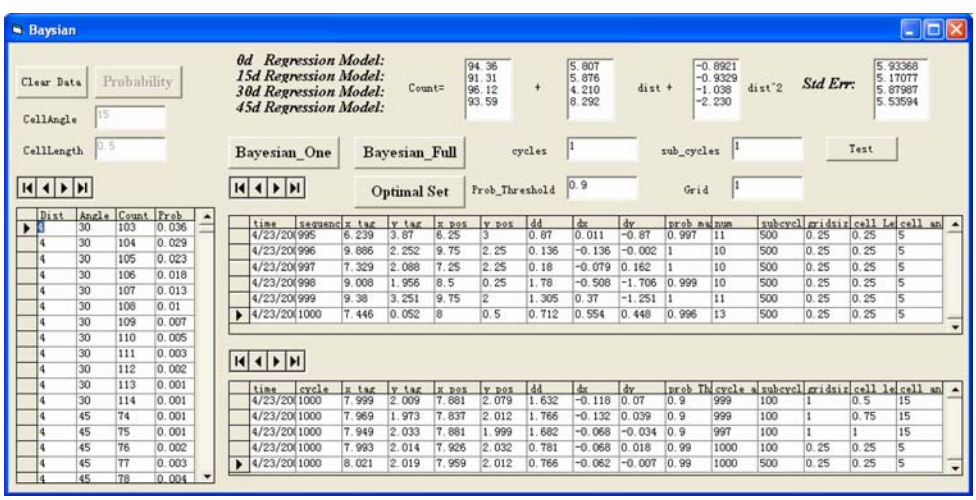

Fig. 7 Program interface of Bayesian inference module

between signal strength and the distance. To ensure the performance of localization algorithms, the environment dynamics need to be taken into consideration.

3. Each localization approach has its own strengths and weaknesses. For instance, nearest-neighbor is not sensitive to the environment and requires less computation effort, but it heavily relies on the placement and the density of the reference nodes. Bayesian inference can update the location dynamically and requires less reference nodes, but it requires more computation time due to iteration operations. Integration of two or more algorithms may bring benefits such as the improvement on accuracy and the reduction on computation time simultaneously.

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