Relative Location in Wireless Networks

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Abstract

In ad-hoc networks, location estimation must be designed for mobility and zero-configuration. A peer-to-peer relative location system uses pair-wise range estimates made between devices and their neighbors. Devices are not required to be in range of fixed base stations, instead, a few known-location devices in the network allow the remaining devices to calculate their location using a maximum-likelihood (ML) method derived in this paper. This paper presents simulations using both a standard channel model and actual indoor channel measurements for verification. Both simulation and measurements show that a peer-to-peer relative location system can provide accurate location estimation using received signal strength (RSS) as a ranging method.

1. Introduction

In many proposed applications for wireless peer-to-peer and ad-hoc networks, knowing the location of the devices in the network is key. For ad-hoc networking, researchers have proposed using location information for routing purposes [6]. For military, police, or fireman radio networks, knowing the precise location of each person with a radio can be critical. In offices and in warehouses, object location and tracking applications are possible with large-scale ad-hoc networks of wireless tags. Finally, for wireless sensor networks that have a variety of home, industrial, and agricultural applications, knowledge of sensor location is critical.

Motorola has introduced the concept of *NeuRFon*^{TM} systems to describe a wireless sensor network in which distributed RF devices operate in analogy to human neurons. These systems are composed of devices that sense, process, transceive, and act in a distributed, low power network. Devices communicate with neighboring devices to pass around, condense, and make decisions based on information they have collected. NeuRFon^{TM} devices, to be fault tolerant, are deployed more densely than necessary in the environment of interest. Location information in these systems will be critical both for identification, information fusion, and localized reactions to stimuli. The location of a sensor may replace ID numbers as the means for addressing sensors [10].

1.1. Exisiting Positioning Systems

The Global Positioning System (GPS) has been suggested as a means to obtain location information in ad-hoc networks [6]. For outdoor applications in which device density is low, and cost is not a major concern, GPS is a viable option. However, adding GPS capability to each device in a dense network is expensive. Furthermore, achieving high accuracy from GPS requires use of differential techniques.

Local positioning systems (LPS) deploy a grid of RF base stations that communicate with devices and then triangulate to determine their locations based on received signal strength (RSS), time difference of arrival (TDOA), or time-of-arrival (TOA) technologies [13]. In LPS, devices communicate only with fixed base stations. When one device is to be located, all other devices are ignored, and the network of base stations calculates the position of the single device based on the measurements (RSS or TOA) made in one or more device-to-base station links. Such an idea could be used in a large scale sensor network in combination with GPS. Since the cost of including GPS capability in every node would be too expensive, GPS could be included in just a fraction of devices [8]. Devices without GPS would range themselves to the devices with GPS functionality. However, as the fraction of GPS functionality decreases, the range of the devices must be larger, and the power drain at the GPS-functional device increases.

2. Peer-to-Peer Relative Location

Another way to obtain relative location in a network is to use pair-wise range estimates made between all devices. In [1] and [2] range estimates are used to draw lines between pairs of devices. One difficulty using these geometric methods is that as more and more devices are added into the location map, the range errors can add onto each other. In [2], a residual weighting algorithm from [3] is used to remove TOA ranges that appear to be due to non-line-of-sight (NLOS) errors. All possible combinations of estimated ranges are tested to find a MSE solution. But in a peer-to-peer network, the possible combinations of pair-wise ranges will rise very rapidly with increasing numbers of devices.

In this paper, we consider the use of ML techniques to accurately locate all devices in the network. First, we define devices in the network as either *reference devices*, which have an independent estimate of their coordinates, or *blindfolded devices*, those that do not. Reference devices might obtain these coordinates from GPS if they have that capability and they have a clear view of the sky. In an indoor system, some reference devices could be fixed as beacons throughout a building. Or, a stationary device with a high degree of confidence in its location estimate could become a reference device. When a device is incapable of being a reference device, it reverts to being a blindfolded device. Blindfolded devices cannot 'see' their location, but they are capable of calculating their range to other blindfolded and reference devices, and transmitting and receiving pair-wise range estimates to and from other devices. With the combined range information between many pairs of devices and the known locations of a few reference devices, a ML solution for the location of all of the blindfolded devices is determined.

Four components must be present in order to make location estimates in a peer-to-peer relative location system. First, some of the devices must be reference devices, so there must be an independent method for absolute location. Second, all of the devices must be able to estimate the range between themselves and their neighbors. Third, there must be an ad-hoc network protocol by which the devices can pass along range and location estimates to other devices. Finally, there must be a *location mapping* algorithm that estimates the locations of the blindfolded devices given the pair-wise range estimates and the known coordinates of the reference devices. This paper assumes that the first three parts exist and focuses on the location mapping algorithm. However, derivation of the algorithm begins with statistics of the ranging method.

3. Range Estimation

In a network of asynchronous devices, TOA range estimation is made by using two-way delay methods [4] and [7]. In two-way TOA, the range estimate will be degraded by the multipath and noise in the channel and the inaccuracies of device reference clocks. The errors due to multipath can be reduced by using very wide bandwidths or radar-like technologies such as ultra-wideband (UWB). However, the range estimate is limited by clock inaccuracies, which can be brought down by using expensive low parts-per-million (PPM) and low phase noise oscillators. For dense networks of low cost, low power wireless devices, it would be advantageous if RSS could be used to make range measurements. RSS can be implemented in simple devices. Although traditionally seen as a crude distance estimator, RSS is less inaccurate at short ranges. A frequently reported model for the fading channel gives the mean dB received power at device i that was transmitted from device j as:

$$\begin{aligned} p_{i,j} &= p_0 - 10n\log_{10}\left(\frac{d_{i,j}}{d_0}\right) \qquad (1) \\ d_{i,j} &= \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2}, \end{aligned}$$

where p_0 is the received power in dB at a reference distance d_0 and n is the path loss exponent [5]. The measured power, in error due to fading, is $\hat{p}_{i,j} = p_{i,j} + X_\sigma$. The random variable, X_σ, represents the medium-scale fading in the channel and is typically reported to be zero-mean and Normal (in dB) with variance σ_{dB}^2 invariant with range [5]. In such a channel, we assume that small scale fading effects have been diminished by use of time-averaging or spread-spectrum techniques such that they do not significantly change the distribution of X_σ from the log-normal distribution of the medium-scale fading. Thus the range estimate, $\hat{d}$, is

$$\hat{d}_{i,j} = d_0 \cdot 10^{\frac{p_0 - \hat{p}_{i,j}}{10n}} = d_{i,j} \cdot 10^{\frac{X_\sigma}{10n}}. \qquad (2)$$

The error in range estimation, $\hat{d}_{i,j} - d_{i,j}$, is proportional to range. To take advantage of the accuracy of RSS at short ranges, a traditional LPS would have to deploy a dense grid of base stations. A peer-to-peer relative location system takes advantage of this characteristic when devices estimate the distance to their neighbors. In a dense network (in which inter-device distances are smaller than the desired location accuracy), RSS range estimation works well.

4. Maximum Likelihood Formulation

In an RSS relative location system, each device measures the received powers from the devices with which it communicates. The device averages these over time and periodically updates a network computer when a received power changes significantly. This network processor compiles the pairwise received power estimates into a matrix P with elements $\hat{p}_{i,j}$ representing the power received by device i that was transmitted from device j. For the ML formulation, one first postulates the coordinates of the N devices and then calculates the posulated received power, $p_{i,j}$, based on Eq. 1. The likelihood L_{in} is the probability, given that the postulated location estimates are correct, that the received power matrix P would be received (within some Δp):

$$L_{in} = \prod_{i=1}^{N} \prod_{\substack{j \in H_i \\ j \neq i}} \left\{ \exp\left[-\frac{1}{2} \left(\frac{p_{i,j} - \hat{p}_{i,j}}{\sigma_{dB}} \right)^2 \right] \Delta p \right\}, \quad (3)$$

where H_i is the set of neighboring devices that device i detected. It is assumed that if a received power goes below a threshold p_{thr}, then the device will not be detected. This information is also useful for a location algorithm. The likelihood function L_{out} is the probability, given that the postulated location estimates are correct, that the received powers for $j \not\in H_i$ were below p_{thr}:

$$L_{out} = \prod_{i=1}^{N} \prod_{\substack{j \notin H_i \\ j \neq i}} \left\{ Q\left[\frac{p_{i,j} - \hat{p}_{thr}}{\sigma_{dB}} \right] \right\}, \quad (4)$$

where $Q[x]$ is the area in the tail of the normal distribution x standard deviations away from the mean. The overall likelihood function is the product of L_{in} and L_{out}. To simplify this product, plug in Eqs. 1 and 2, take the negative logarithm of the result and find the minimum. The ML coordinates are given by

$$\{X, Y, Z\} = \arg \min_{X,Y,Z} \left[f(x_k, y_k, z_k) \right] \quad (5)$$

$$f(x_k, y_k, z_k) = \quad (6)$$
$$\frac{b^2}{8} \sum_{i=1}^{N} \sum_{\substack{j \in H_i \\ j \neq i}} \ln^2 \frac{\hat{d}_{i,j}^2}{d_{i,j}^2} - \sum_{i=1}^{N} \sum_{\substack{j \notin H_i \\ j \neq i}} \ln \left[Q\left(\frac{b}{2} \ln \frac{d_{thr}^2}{d_{i,j}^2} \right) \right]$$

$$\begin{aligned} b &= 10n/(\ln(10)\sigma_{dB}) \\ d_{thr} &= d_0 \cdot 10^{(p_0 - p_{thr})/(10n)}. \end{aligned} \quad (7)$$

To find the minimum of Eq. 6, a conjugate gradient algorithm is used [9]. The algorithm is aided by the fact that Eq. 6 is readily differentiable.

5. Simulation

The performance of peer-to-peer relative location is simulated for an indoor factory area in 2-D using Matlab. Reference devices are positioned in the corners of a 15m by 15m area, and N blindfolded devices are positioned randomly (uniformly distributed) within the area. The simulation then randomly generates the received power between all pairs of devices in the area. Eq. 1 with $n = 2.6$ and a dB standard deviation of $\sigma_{dB} = 7.1$ is used to simulate a factory environment [11]. Any received powers below p_{thr} are erased from the received power matrix P to simulate the range limit d_{thr} of the devices. The simulations are run for both $d_{thr} = 20$m and $d_{thr} = \infty$ (when all devices are in range of each other).

Once the received powers are generated for the devices, the central processor guesses the initial coordinates for each blindfolded device. This simulation uses the range estimates between blindfolded and reference devices and the method of [12]. If a blindfolded device is not in range of at least 3 reference devices, the simulation generates a random guess (although accurate initial postulated coordinates may speed up the minimization, it is not essential). After the conjugate gradient algorithm finds a maximum in the likelihood function (minimum in Eq. 6), the location estimates are compared with the actual locations and the errors are recorded. These location estimates are sometimes not the global maximum, however, from closely analyzing several of the simulation runs, it seems that the errors due incorrectly identifying a local maximum are not severe. For $N = 1$, 5, 10, 15, 20, 25, 30, 35, and 40, the number of trials is 1000, 800, 400, 250, 200, 160, 100, 100, and 100, respectively (at low N more trials are necessary to generate as many location errors). The 67th percentile of the blindfolded device location errors is plotted in Fig. 1.

6. Measurement Verification

It is assumed in the simulation that the fading X_σ between a device and each of its neighbors is statistically independent, since we are aware of no channel model in the literature that addresses link fading correlations in a peer-to-peer network. Thus verification of the simulation requires actual RSS channel measurements, which are conducted in the Motorola facility in Plantation, Florida. The measurement system consists of a HP 8644A signal generator transmitting a CW signal at 925 MHz at an output level of 0.1 mW and a Berkeley Varitronics Fox receiver. A $\lambda/4$ dipole with Roberts balun resonant at 925 MHz is positioned at a

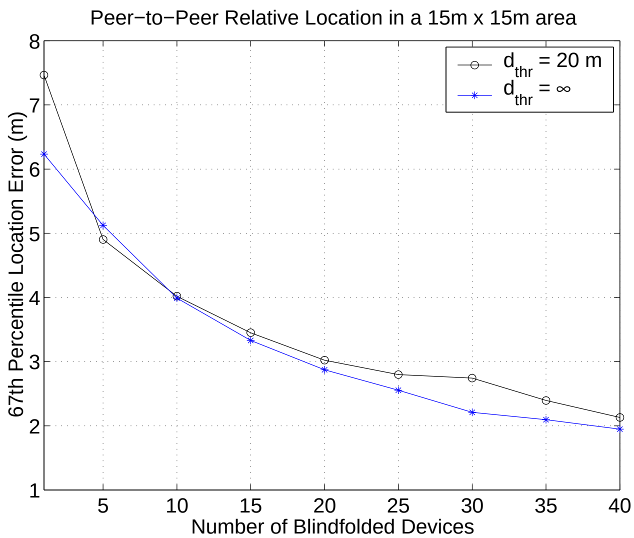

Figure 1. Simulated 67^{th} percentile errors

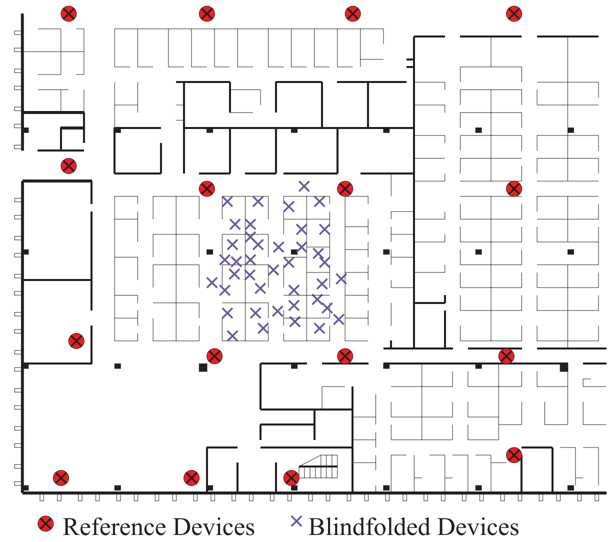

Figure 2. Floor plan of measurement area

height above the floor of 1 meter at both the transmitter and receiver. The antennas are both stationary during each measurement and have an omnidirectional radiation pattern in the horizontal plane and a vertical beamwidth of 30^o. The Fox receiver was set to average received power over one second. The campaign is conducted during evenings and on weekends to ensure that the channel is mostly static during the measurements. Two meter tall Hayworth partitions and ceiling-height interior walls divide the area into cubicles, lab space, and offices. To simulate a system in which reference devices are placed approximately every 15 m in the indoor environment, they are placed in a 4 by 4 grid in the measurement area (see map in Fig. 2).

Forty locations are chosen for the blindfolded devices in the center quadrant (16 m by 14 m). The center quadrant consists of four columns of cubicles and the hallways that separate them. Two or three blindfolded device locations are chosen for each cubicle, and a few locations put into the hallways. This density or greater would be expected in a location and tracking system in which each employee places a tag on two or three valuable things that he or she works with, such as computers and accessories, electronic equipment, briefcases, wireless phones, notebooks, tools, or key rings. Together, there are 56 reference and blindfolded device locations.

First, the transmitter is placed at location 1, and received power readings are taken and recorded at locations 2 through 56. Next, the transmitter is moved to location 2, and power readings are taken at locations 1 and 3 through 56. This process continues until power measurements have been made between each pair of devices, for a total of 3080 RSS measurements. The measured received powers, plotted in Fig. 4, fit the channel model of Eq. 1 with a d_0 of 1 m, n of 2.98. The histogram of X_σ shows a Gaussian PDF with a standard deviation of $\sigma_{dB} = 7.38$.

The ML location is calculated using the measured matrix P by the method in Section 4 and the results are shown in Fig. 3. The RMS location error for all 40 blindfolded devices is 2.1 meters. Of the 33 devices located in cubicles, 22 are estimated to be within the correct cubicle, and the remaining 11 are estimated to be either in the immediate neighboring cubicle or in the hallway just outside the correct cubicle. The maximum error is 4.2 m, the median error is 1.8 m, and the minimum error is 0.12 m.

7. Conclusions

Relative location has several advantages over LPS. Higher density of blindfolded devices actually increases the accuracy of the location system. High reference device density, however, is not necessary. In fact, blindfolded devices not in range of any reference devices can be located. As a result, devices can use low transmit power for purposes of detection avoidance, low interference and high capacity, or for extending battery life. Reference devices, if they are fixed at known locations, do not need to be any more complicated or expensive than the transceiver devices that serve as tags for the items being tracked. Even if reference devices use GPS, then the ratio of devices that need to be GPS-capable can be very low without increasing the load on the

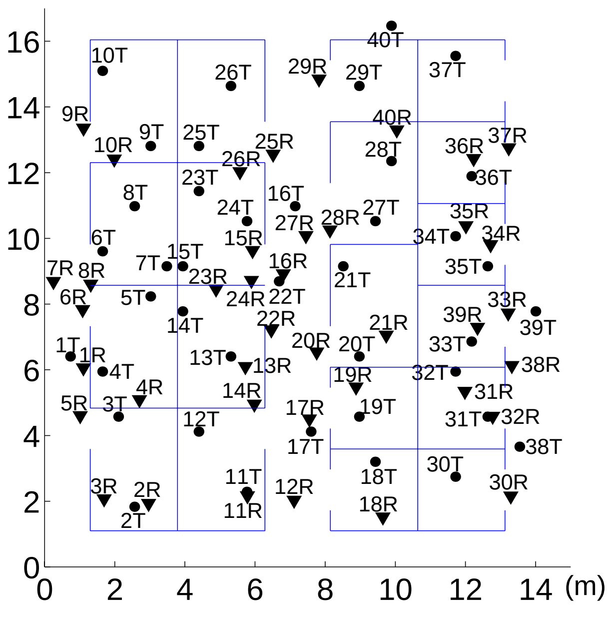

Figure 3. True location (T) and relative location system estimate (R)

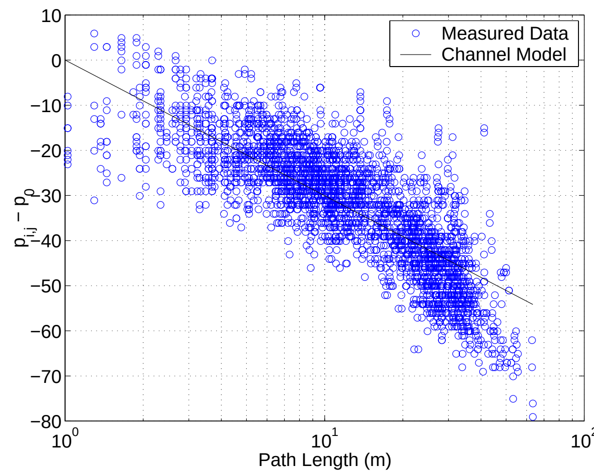

Figure 4. Measurements fit channel model

GPS-capable devices.

This paper has presented a ML method to calculate device locations given pair-wise received power measurements and reference device coordinates. This method has been used in simulations to show the relationships between device densities and location accuracy. It has been demonstrated using RSS measurements in a cluttered office environment to show that a simple indoor location and tracking system can locate devices to within the correct cubicle 67% of the time. Although RSS range estimates are often in error, short range operation and built-in redundancies help correct them. With higher device densities, or with more accurate two-way TOA ranging methods, relative location could bring even higher accuracies.

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