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Statistical Location Estimation in Container-Grown Seedlings Based on Wireless Sensor Networks

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Abstract

This paper presents a sensor location decision making method respect to Container-Grown Seedlings in view of precision agriculture (PA) when sensors involved in tree container measure received signal strength (RSS) or time-of-arrival (TOA) between themselves and neighboring sensors. A small fraction of sensors in the container-grown seedlings system have a known location, whereas the remaining locations must be estimated. We derive Rao-Cramer bounds and maximum-likelihood estimators under Gaussian and log-normal models for the TOA and RSS measurements, respectively.

Keywords: *Container-Grown Seedlings, Wireless Sensor Network, Sensor Position Location, Signal Strength, Time-of-Arrival, Rao-Cramer bound.*

1. Introduction

Emerging applications for wireless sensor networks will depend on automatic and accurate location of thousands of sensors. In sensing applications of the container-grown seedlings such as water quality monitoring, precision agriculture, and air quality monitoring, sensing data without knowing the sensor location is meaningless [3]. In addition, by helping reduce configuration requirements and device cost, relative location estimation may enable applications such as inventory management, intrusion detection, and traffic monitoring, and locating emergency workers in buildings. To design a relative location system that meets the needs of these applications, several capabilities are necessary. The system requires a network of devices capable of peer-to-peer range measurement, an ad-hoc networking protocol, and a distributed or centralized location estimation algorithm. For range measurement, using received signal strength (RSS) is attractive from the point of view of device complexity and cost but is traditionally seen as a coarse measure of range. Time-of arrival (TOA) range measurement can be implemented using inquiry-response protocols [2]. In this paper, we show that both RSS and TOA measurements can lead to accurate location estimates in wireless sensor networks respect to the container-grown seedlings.

2. Sensor Based Container-Grown Seedlings

Figure 1 illustrates M2M communication network architecture. A machine is known as a machine type communication (MTC) device. The MTC devices communicate with each other and send data to the MTC gateway of M2M area networks through multi-hop communications. The MTC gateway again transmits data to the backhaul core networks through MTC routers having a large communication range. Hundreds of low

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cost, energy and computational power wireless sensor nodes are mostly used as MTC devices in the M2M area networks since sensors can be deployed easily, controlled automatically and monitored remotely. Moreover, sensors include low power radio and power management mechanisms to conserve energy for a longer time network operation. Hence, sensors are used as the integral part of M2M communication networks for different monitoring applications especially, agricultural monitoring [1].

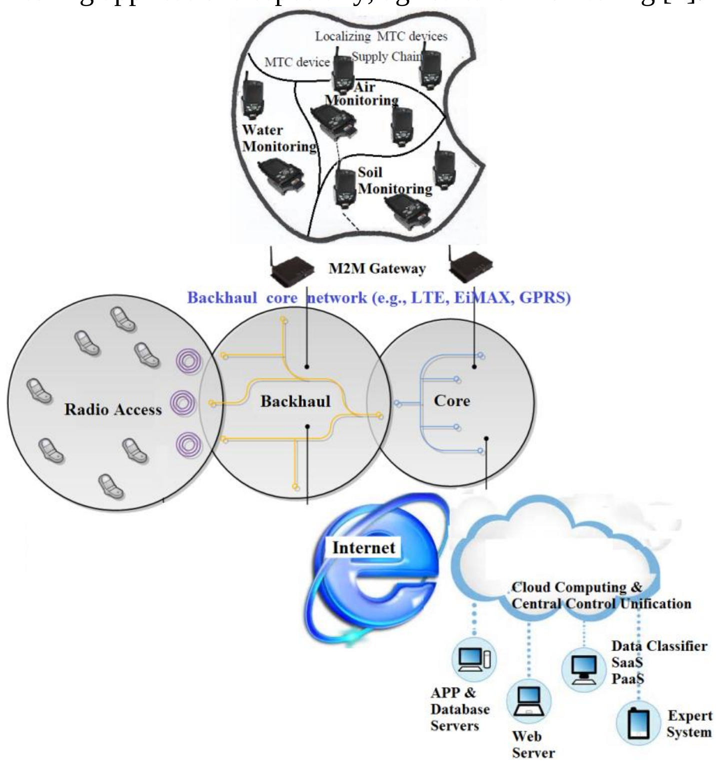


Figure 1. Sensor-based M2M networks of Container-Grown Seedlings

3. Sensor Location Determination

We consider a network of m reference and n blindfolded devices. The device parameters D = [d_1, …, d_{m+n}], where d_i is a location vector. The location problem is to estimate the blindfolded device coordinates $P = [P_x, P_y]$, where $P_x = [x_1, \dots, x_n]$, $P_y = [y_1, \dots, y_n]$, given the known reference coordinates $[x_{n+1}, \dots, x_{n+m}, y_{n+1}, \dots, y_{n+m}]$. In TOA, $X_{ij} = T_{ij}$ is the measured value between sensor i and j in seconds, and in RSS, $X_{ij} = P_{ij}$ is the measured received power at sensor i transmitted by device j in milliwatts. Only a subset of devices makes pair-wise measurements with sensor k, and T and P are taken to be upper triangular matrices, and these measurements are assumed statistically independent. Assume that T_{ij} is normally distributed with mean m_{ij}/c and variance s^2, where $m_{ij} = \|d_i - d_j\|^{1/2}$, and c is the speed of propagation. We assume that P_{ij} is log-normal. Then, the maximum likelihood estimator (MLE) of range m_{ij}, given received power P_{ij}, is the following.

$$\hat{m}_{ij} = r_0\left(P_0 / P_{ij}\right)^{1/n_p} \tag{1}$$

Here, P_0 is the received power in decibel mill watts at a reference distance r_0, and it is calculated from the free space path loss formula [4]. The path loss exponent n_p is a function of the environment. For particular environments, n_p may be known from prior measurements.

The CRB gives a lower bound on the ensemble variance over different random shadowing environments. If networks with the same relative device coordinates are implemented in many different areas, the variances of any unbiased coordinate estimator will be lower bounded. We denote by F_R and F_T the Fisher information matrices (FIMs) for the RSS and TOA measurements, respectively. Each sensor has two parameters, and we can see that the FIM will have the following form, if partitioned into blocks.

$$F_R = \begin{bmatrix} R_{xx} & R_{xy} \\ R_{xy}^T & R_{yy} \end{bmatrix}, F_T = \begin{bmatrix} T_{xx} & T_{xy} \\ T_{xy}^T & T_{yy} \end{bmatrix} \quad (2)$$

Here, R_{xx} and T_{xx} are given by $F_P = -E\nabla_P(\nabla_P\, l(X|D))^T$ using only the x parameter vector P_x, and R_{yy} and T_{yy} are given by using only P_y. Assume all devices make pair-wise measurements with every other device, i.e., $H(k)=\{1, 2, \ldots, k\text{-}1, k+1, \ldots, m+n\}$. The off-diagonal blocks are similarly derived. For the case of RSS measurements, the elements of R_{xx} are given by

$$R_{xx}(k,l) = \begin{cases} \sum_{i\in H(k)} \frac{b(x_k - x_i)^2}{\| d_k - d_i \|^4}, & k = l \\ -I_{H(k)}(l)\frac{b(x_k - x_l)^2}{\| d_k - d_l \|^4}, & k \neq l \end{cases} \quad (3)$$

Similarly, R_{xy} and R_{yy} are defined. In the log of the joint conditional probability density function, The second partial of (i, j) -element ($i\neq j$) is $-1/(c^2 s^2)$. So, for the case of TOA, the elements of T_{xx} are given by

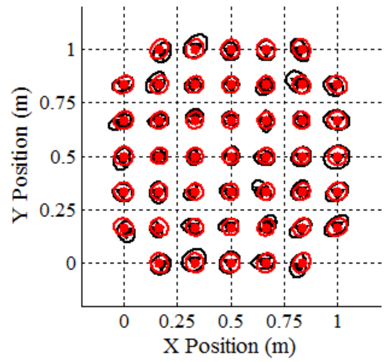
$$T_{xx}(k,l) = \begin{cases} \sum_{i\in H(k)} \frac{(x_k - x_i)^2}{c^2 s^2 \| d_k - d_i \|^2}, & k = l \\ -I_{H(k)}(l)\frac{(x_k - x_l)^2}{c^2 s^2 \| d_k - d_l \|^2}, & k \neq l \end{cases} \quad (4)$$

For the TOA measurements, the dependence on the device coordinates is in unit-less distance ratios, indicating that the size of the system can be scaled without changing the CRB as long as the geometry is kept the same. However, in the case of RSS measurements, the variance bound scales with the size of the system even if the geometry is kept the same due to the terms in the denominator of each term of R. For the case of one blindfolded device, a simple expression for unbiased estimators can be derived for both RSS and TOA measurements. In the cases of TOA and RSS, the MLEs are

$$\hat{P}_{TOA} = \arg\min_{\{d_i\}} \sum_{i=1}^{m+n} \sum_{i\in H(i)} \left(cT_{ij} - \| d_i - d_j \|\right)^2,\ j < i \ \text{,}\ \hat{P}_{RSS} = \arg\min_{\{d_i\}} \sum_{i=1}^{m+n} \sum_{j\in H(i)} \left(\ln \frac{\hat{m}_{ij}^2}{\| d_i - d_j \|^2}\right)^2,\ j < i \quad (5)$$

4. Channel Measurement simulation

A set of multipoint-to-multipoint wideband channel measurements were conducted at famous container-grown seedlings company in Korea. Forty-five device locations are identified within a 1 by 1 m area and marked with tape. The measurement system uses a wideband direct sequence spread-spectrum (DS-SS) transmitter (TX) and receiver (RX). The TX and RX are battery-powered and are placed on carts. The TX outputs an un-modulated pseudo-noise (PN) code signal with a 40-MHz chip rate and code length 1024. The center frequency is 2443 MHz, and the transmit power is 10mW. Both TX and RX use 2.4-GHz sleeve dipole antennas kept 1m above the floor. The antennas have an omnidirectional pattern in the horizontal plane and a measured antenna gain of 1.1 dBi. The RX records I and Q samples at a rate of 120 MHz, down converts, and correlates them with the known PN signal and outputs a power-delay profile (PDP). Four devices near the corners are chosen as reference devices. The remaining 45 devices are blindfolded devices. The four reference device coordinates and either the RSS or TOA measurements or are input to the MLE. The minimum in each case is found via a conjugate gradient algorithm. Then, the estimated device locations are compared with the actual locations in figure 2. We simulated a relative location system by generating random measurements and maximizing the likelihood function. After many trials, we showed the results vs. the Cramer-Rao Bound. Figure 3 denotes the true (•) and estimated (▼) location using RSS data for measured network with four reference devices. The RMS location error of all 45 unknown-location devices is 0.061m in the RSS case and 0.0569m in the TOA case. The RMS CRB is lower bounded by 0.0575m for the RSS and TOA cases.



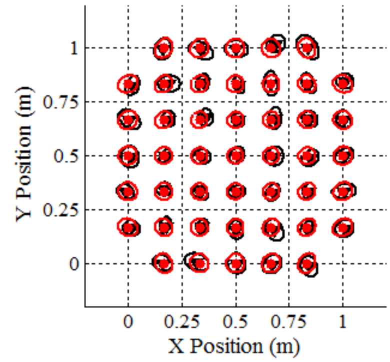


Figure 2. True and estimated location using RSS and TOA data for measured network

5. Conclusion

This paper began by proving that location estimation variance bounds (CRBs) decrease as more devices are added to the network. Next, it was shown that CRBs can be readily calculated for arbitrary numbers and geometries of sensors. Sensor location estimation with approximately 0.06m RMS error has been demonstrated using RSS and TOA measurements. Fading outliers can still impair the RSS relative location system, implying the need for a robust estimator.

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