Sensor Location Estimation in of Landscape Plants Cultivating System (LPCS) Based on Wireless Sensor Networks with IoT

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Abstract

In order to maximize the production of landscape plants in optimal condition while coexisting with the environment in terms of precision agriculture, quick and accurate information gathering of the internal environmental elements of the growing container is necessary. This may depend on the accuracy of the positioning of numerous sensors connected to landscape plants cultivating system (LPCS) in containers.

Thus, this paper presents a method for estimating the location of the sensors related to cultivation environment connected to LPCS by measuring the received signal strength (RSS) or time of arrival TOA received between oneself and adjacent sensors.

The Small sensors connected to the LPCS of container are known for their locations, but the remaining locations must be estimated. For this in the paper, Rao-Cramer limits and maximum likelihood estimators are derived from Gaussian models and lognormal models for TOA and RSS measurements, respectively.

As a result, this study suggests that both RSS and TOA range measurements can produce estimates of the exact locations of the cultivation environment sensors within the wireless sensor network related to the LPCS.

Keywords: Sensor Location Estimation, Landscape Plants Cultivating System (LPCS), Wireless Sensor Networks, Received Signal strength (RSS), Time of Arrival (TOA)

1. Introduction

The present, most of Korea's landscape plants farms are cultivated on the open land [1]. The open land cultivation method produces landscape plants, which is difficult to achieve uniform quality, and it is difficult to transplant or replace poor soil at an inappropriate time. Therefore, the efficiency of production is not improving. In order to improve this point, the need for container cultivation is emphasized, and in advanced countries, the mechanization of each production process, container cultivation, scientific methods, especially the recent convergence with ICT technology, to improve annual income for farmers who produce under the container landscaping production system. However, in Korea, it is only implemented in some enterprise-sized landscape plants farms [1]. Therefore, most of the studies on landscape plants cultivating are focused on the effects of container cultivation by comparing it with the open land cultivation, and, there is a lack of research on designing and developing container cultivation systems that converging ICT technology.

As above, Korea's landscape plants production technology is the least developed among agriculture field, but it is necessary to increase landscape plants productivity by quickly introducing convergence technology

methods such as precision agriculture and smart farms, which have been actively introducing ICT technology convergence in the agricultural field.

In the case of precision agriculture, it is an agricultural production system that considers 'Doing the right treatment, at the right times, in the right place' in the 1980s, and has procedures called information collection, interpretation, and application of interpreted information. First, information about the agricultural environment, such as the location of soil, soil condition, vitality of crops, yield, etc. is collected. Next, information is interpreted and aggregated to calculate soil preparation conditions, etc. that will optimally produce crops [2]. Finally, sowing, fertilizer injection, irrigation water and pesticide injection are performed in real time under the optimal conditions. By applying the input time and amount accurately, the input cost is reduced to the minimum, output is improved to the maximum, and more eco-friendly operation is possible. This precision agriculture had recently developed into concepts such as smart agriculture and smart farm, which combines information and communication technology (ICT) with existing agriculture [3], and automatic and accurate real-time information gathering is a key point of minimum cost and maximum effect. For this purpose, it is essential to know the exact location of sensors for collecting information.

Smart Farm means a farm that uses IoT technology to monitor information about the cultivating environment, such as temperature, humidity, and CO_2, and to control the environment that can be kept optimized for the cultivating environment [4]. Therefore, it is essential to collect fast and accurate environmental information on various attached sensors such as temperature, humidity, air flow, heat detection, and intrusion detection inside the greenhouse. It may also be possible to estimate the exact location of numerous sensors inside the greenhouse.

As above, the accuracy of application implementation based on the wireless sensor network depends on how automatic and accurate the location of numerous sensors is. In particular, it is meaningless to detect and collect various information of the landscape plants cultivating environment, such as water quality monitoring, air quality monitoring, soil environment monitoring, precision agriculture, etc., without knowing the location of sensors measuring the cultivation environment [5] in landscape plants cultivating system (LPCS). Here LPCS means a wireless network-based total cultivation management system(CMS) that can receive accurate cultivation environment information and optimal manage in real time through an accurately estimated location for numerous sensors that measure cultivation environment information; temperature, humidity, soil environment, insect damage, tree growth, etc., in a plants cultivation container, such as a smart farm.

Several functions are needed to design a relative location system that meets the different needs of these applications. First, it requires networks of devices capable of measuring peer to peer (P2P) ranges, second ad-hoc networking protocols, and thirdly distributed or centralized positional estimation algorithms. For range measurements, the use of the received signal strength (RSS) is attractive in terms of device complexity and cost, but is considered to be a rough measurement. Range measurements through) the time of arrival (TOA) can be made using the Response-Inquiry protocol [6].

The purpose of this study is to propose a way to estimate the most necessary the exact location of environmental information sensors in order to receive accurate cultivation environment information in real time on LPCS and to carry out immediate management thereof.

As a result, this study suggests that both RSS and TOA range measurements can produce estimates of the exact locations of the cultivation environment sensors within the wireless sensor network related to the cultivation container of the landscape plants.

2. Sensor-based Landscape Plants Cultivating System

Figure 1 shows sensor network composition of sensor-based landscape plants cultivating system (LPCS). LPCS is a sensor-based cultivating system that collects environmental information; water quality, air quality, soil quality, insect damage information, arboretum growth status, etc., in real time by attaching numerous sensors by type of cultivation environment in containers for landscape plants.

The collected information is communicated to each other through a machine type communication (MTC) device and sent to central control unification by the Wireless Communication network. The real-time information of the cultivation environment collected here is classified and analyzed and the optimal

Hundreds of low-cost, energy and computer power wireless sensor nodes are mainly used as MTC devices in the sensor network because sensors can be easily deployed, controlled and monitored remotely. Furthermore, sensors include low-power radios and power management mechanisms to save the energy needed for long-term network operations. Therefore, sensors are used as an integral part of the sensor network, especially for a variety of monitoring applications, such as monitoring landscape environment information [7].
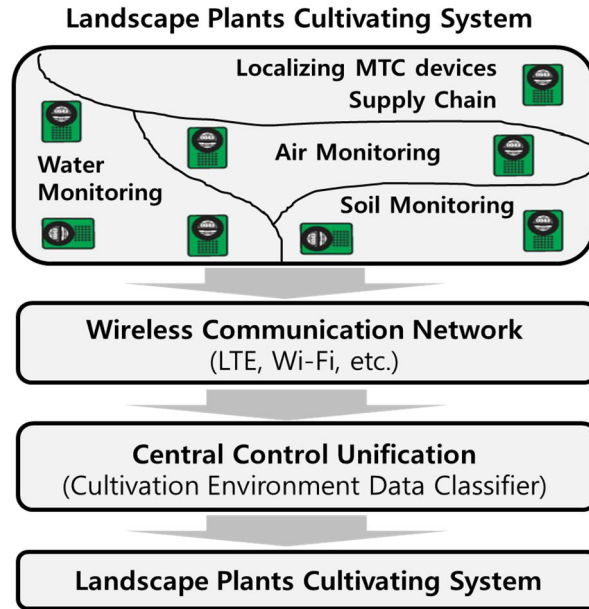

Figure 1. IoT Network Composition of Sensor-based Landscape Plants Cultivating System

3. Sensor Location Estimation

In this study, m reference devices that already know their locations and n invisible devices should be considered together. Device Parameter D = $[d_1, \ldots, d_{m+n}]$, where d_i is a location vector. The problem with location is to estimate coordinate $P = [P_x, P_y]$ of invisible devices, here $P_x = [x_1, \ldots, x_n]$, $P_y = [y_1, \ldots, y_n]$, coordinates of known reference devices $[x_{n+1}, \ldots, x_{n+m}, y_{n+1}, \ldots, y_{n+m}]$. For TOA, $X_{ij} = T_{ij}$ is the measured power in seconds between sensor i and j, and for RSS, $X_{ij} = P_{ij}$ is the measured power transmitted by device j in mW and received from sensor i. Only a few devices perform pair-wise measurements using senso k, T and P are considered to be the upper triangle matrix, and these methods of measurement assume statistically independently.

It is generally assumed that T_{ij} is distributed with mean m_{ij}/c and variance s^2, where $m_{ij} = \|d_i - d_j\|^{1/2}$, c is propagation speed.

It is also assumed that P_{ij} is the log-normal distribution. The maximum likelihood estimator(MSE) m_{ij} and the given receiving power P_{ij} are then as followes for the following categories:

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

Where P_0 is the power received from reference r_0 to dBm and is calculated by the free-space path loss (FSPL) formula [8]. Path Loss index n_p is an environmental function. For certain environments, n_p is known by pre-measurement.

The CRB provides a lower bound on the ensemble variance over different random shadowing environments [9]. In many different areas, the variance of unbiased coordinate estimators is lower when a network with the same relative device coordinates is implemented. F_R and F_T represent Fisher information matrix (FIMs) for RSS and TOA measurements, respectively. Each sensor has two parameters, and when the FIM is divided into blocks, it will be seen the following form.

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

where R_{xx} and T_{xx} use only x parameter vector P_x to give $F_P = -E\nabla_P(\nabla_P \, l(X|D))^T$, and R_y and T_{yy} use only P_y. Suppose all devices are measured in pairs with all other devices, such as, $H(k)=\{1, 2, ..., k-1, k+1, ..., m+n\}$. The off-diagonal blocks are likewise derived. For RSS measurements, the elements of R_{xx} are as follows:

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

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

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

For TOA measurements, the dependence on device coordinates indicates that the system can be resized without changing the CRB as long as the geometry remains the same for the unit distance ratio. However, for 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. A simple expression for unbiased estimator, for one blindfolded device can be derived for both RSS and TOA. For TOA and RSS, the MLEs are as follows.

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

4. Simulation

A multipoint-to-multipoint broadband channel measurement set was conducted by a leading container cultivation seedling company in Korea. The 45 unit positions are identified and marked with tape within the 1 by 1 m area. The measurement system uses wide-band direct sequence spread-spectrum (DS-SS) transmitter (TX) and receiver (RX). The TX and RX are battery-powered and mounted on the cart. TX outputs unmodified pseudo-noise (PN) code signal of 40 MHz chip speed and code length 1024. The central frequency is 2443 MHz and the transmission power is 10 mW. Both TX and RX have 2.4 GHz sleeve dipole antennas that maintain 1 m above the floor. The antenna has an omni-directional pattern on the horizontal plane with a measured antenna gain of 1.1 dBi. The RX records I and Q samples at a rate of 120MHz, down converts, and

correlates them with the known PN signal and outputs a power-delay profile (PDP). Four devices near the corner are selected as reference devices. The remained other 45 devices are eye-covered devices. It is entered into four reference device coordinates and either the RSS or TOA measurements, or are input to the MLE. The minimum value in each case can be determined by the tolerance gradient algorithm. The expected device position is then compared with the actual position in Figure 2.

We simulated a relative location system that generates random measurements and maximizes likelihood functions. After many trials, we showed the results vs. the Kramer-Lao Bound. Figure 3 shows the true (•) and estimated (▼) location using RSS data for the network measured by the four reference devices. The RMS location error for all 45 unknown location devices is 0.061 m for RSS cases and 0.0569 m for TOA cases. The RMS CRB is the lower limit of 0.0575 m for RSS and TOA cases.
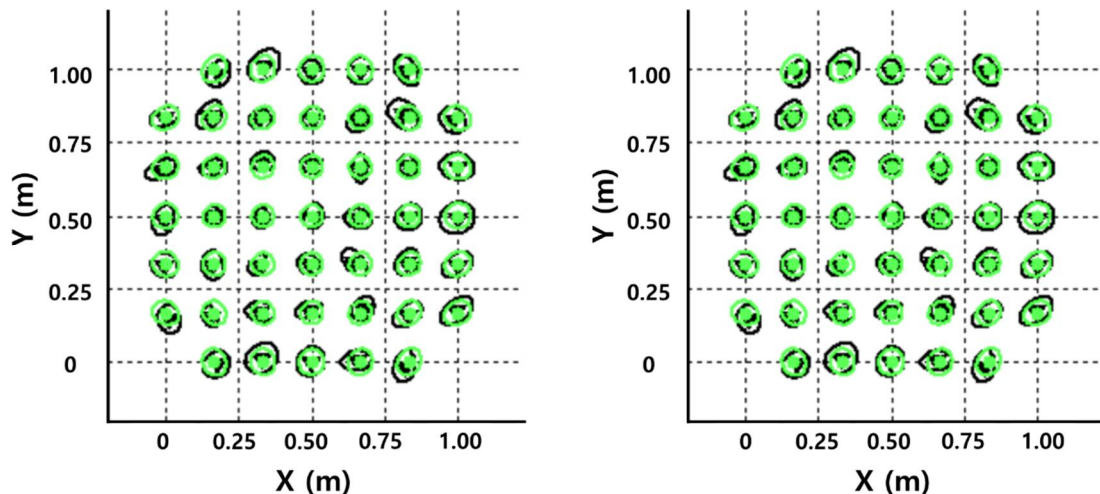

Figure 2. The results of using RSS and TOA data for measured network

5. Conclusion

The purpose of this study is to propose a method for estimating the exact location of the most necessary environmental information sensors in order to receive and immediately analyze and manage accurate cultivation environment information from LPCS in real time.

As a result, this study suggests that both RSS and TOA range measurements can derive accurate positional estimates of cultivation environment sensors within the wireless sensor network associated with landscape plants containers.

This paper began by proving that the more devices are added to the network, the lower the limits of location estimation variance bounds (CRBs). Next, it was shown that CRBs could be easily calculated for arbitrary numbers and geometry of the sensors. Estimation of sensor location of approximately 0.061 m RMS error was demonstrated using RSS and TOA measurements. And it was analyzed that the fading outliers could still damage the RSS relative location system. This suggests the need for a robust estimators.

Currently, technology development and research are insufficient in Korea's landscape plants production technology. However, in the wake of the recent Fourth Industrial Revolution, big data on container cultivation technology and landscape plants maintenance to improve the productivity of landscape plants should be established, and a new turning point should be prepared for landscape plants production by investing in technology development that combines the IoT and AI. The content of this study is valuable in the context of the need for a smart landscaping system, such as a smart farm. Thus, based on this, various studies on more advanced sensor-based landscape plants cultivating system (LPCS) will have to be followed.

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