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Non-parametric location estimation in rough wireless environments for wireless sensor network

Long Cheng[a,b,*], Yan Wang[a,b], Hao Wu[c], Nan Hu[a], Chengdong Wu[a]

[a] School of Information Science and Engineering, Northeastern University, Shenyang 110819, China
[b] Department of Computer and Communication Engineering, Northeastern University, Qinhuangdao 066004, China
[c] Engineering Faculty, University of Sydney, NSW 2006, Australia

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ABSTRACT

With the development of microelectronics, wireless communication and micro-electro-mechanical systems technologies, wireless sensor network (WSN) has received considerable attention. The location information is critical for application of WSN. The high accuracy localization result can be achieved when the propagation environment is line of sight. However, it is decreased extremely in non-line of sight (NLOS) environment. NLOS propagation which affects the accuracy of mobile localization is one of the most important challenges for WSN. In this paper, we propose a method to alleviate the influence of the NLOS error using the improved Kalman filter based on Gaussian mixture distributions (IKF-GMD). The NLOS detection is firstly introduced to identify the propagation condition of the beacon node. For the NLOS measurements, GMD algorithm is proposed to estimate the mean and variance of the measurements and multiple modes combination method is proposed to mitigate the NLOS error. The IKF-GMD approach can effectively mitigate the NLOS error and does not assume any statistical knowledge of the NLOS error. Simulation and experiment results demonstrate that the performance of the proposed IKF-GMD algorithm outperforms the Kalman filter and robust Kalman filter methods.

1. Introduction

Due to the availability of such low energy cost sensors, micro-processor and radio frequency circuitry for information transmission, there is a rapid development of wireless sensor network (WSN) [1]. Since the sensor node is equipped with sensing, processing and communication modules, the WSN can be used in smart environment for some practical purposes (e.g., air pollution, volcanoes, floods, fires, etc.) [2,3].

Global Positioning System (GPS) is the most common positioning system in the world. However, research studies show that the GPS's performance degrades drastically when receiver is located in the indoor or forest environments. The WSN based localization strategy has the features of well flexibility, convenient maintenance and low-cost update. So WSN is increasingly being used. In WSN based localization methods, the main approaches proposed to locate the unknown node (the location is unknown) are based on received signal strength (RSS) [4], angle of arrival (AOA) [5], time of arrival (TOA) [6] or time difference of arrival (TDOA) [7]. If line of sight (LOS) propagation exists between unknown node and all beacon nodes (the location is known), high location accuracy can be achieved using Kalman filtering and least-squares technologies [8]. However, in certain environment, especially in the indoor area, the direct path from the unknown node to a beacon node is blocked by obstacles. The signal measurements include an error due to the excess path traveled because of the reflection or diffusion of signal, which is termed as the NLOS error. The NLOS error results in the large localization estimation error. Therefore the research on the localization in the NLOS environment remains a challenge topic and has highly practical meaning.

The main contribution of this paper is given as follows:

(1) The NLOS detection method is introduced to identify the propagation condition of the beacon node.
(2) For the NLOS measurements, GMD algorithm is proposed to estimate the mean and variance of the measurements. The multiple modes combination method is proposed to mitigate the NLOS error.
(3) The proposed algorithm does not assume any statistical knowledge of the NLOS error. It uses the TOA measurements but can

* Corresponding author at: School of Information Science and Engineering, Northeastern University, Shenyang 110819, China. Tel.: +86 18931347611; fax: +86 02483687761.
E-mail address: chenglong8501@gmail.com (L. Cheng).

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easily extend to other signal features such as TDOA and RSS. Therefore it is independent of the physical measurement ways.

This paper is organized as follows. The related works are described in Section 2. In Section 3 we will introduce the problem statement in which the signal model and Gaussian mixture distributions are introduced. In Section 4 we will introduce our proposed method. Section 5 shows the simulation and experiment results. The conclusions are given in Section 6.

2. Related works

A variety of localization methods have been proposed in NLOS environment. In [9–12], the NLOS identification algorithms have been proposed. These methods are termed as the hard-decision approaches, i.e. these methods identify which measurements are contained by the NLOS error and discarded them for positioning. They attempt to identify the NLOS propagation by using the hypothesis test [9], likelihood ratio test [10] and statistical analysis methods [11,12]. They localize the position of unknown node using LOS measurements. If the identification is correct, the localization accuracy can be achieved. However, the probability of wrong identification is inevitable. The second methods termed as soft-decision [13–17]. They attempt to combine all of the LOS and NLOS measurements to estimate the location of unknown node. The interacting multiple model (IMM) approach with the Kalman filtering technique is developed [13]. And the data fusion based IMM approach is investigated [14,15]. An *M*-estimator [16] is employed to estimate the distribution of NLOS error. And an IMM based cubature Kalman filter [17] is introduced to deal with the maneuvers of the target. In [18], the authors combine the hard-decision and soft-decision method to estimate the position of the unknown node. A NLOS detection algorithm is firstly proposed to discard the large outliers and accepted measurements are weighted with different probabilities. However, most of the methods assume that the distribution or parameters of the NLOS error is known which is impractical.

In [10,19–21], the authors investigate the non-parametric methods to deduce the influence of the NLOS error. The advantage of non-parametric method is that it does not need to know the parameters of the NLOS measurements; namely, it can be used with any of the ranging technologies and does not require prior information about statistical properties of the NLOS measurements. In [10], the authors propose a weighted least squares method which utilizes all NLOS and LOS measurements but provides weighting to minimize the effects of the NLOS contributions in estimating the location of unknown node. Nevertheless, the weighting strategy may provide unreliable results. The robust multilateration method [19] can avoid this problem by minimizing the proposed objective function. In [20], a linear-programming approach to the problem of NLOS mitigation in wireless networks is proposed. This method uses the ranges estimations in LOS to define the objective function and the range estimates in NLOS to restrict the feasible region for the linear program. Since the least squares algorithm estimates the location of unknown node by minimizing the sum of squared residual, one large measurement error induces relatively larger localization error. In [21], authors propose a residual weighting algorithm (Rwgh) which uses the sum of squared residuals of a least squares estimation as the indicator of the accuracy of calculated node coordinates. They apply least squares multilateration on all possible combinations of the distance measurements and then the estimated location is computed as a weighted combination of these intermediate estimates. An adaptive Rao–Blackwellized particle filter [22] is developed in mixed LOS/NLOS conditions, where the statistical parameter of NLOS error is unknown. It uses an analytical method to estimate the mobile state while employing the particle filter to estimate the posterior density of sight conditions and unknown parameters. In [23], a likelihood matrix correction based mixed Kalman and *H*-infinity filter method which is robust to the NLOS errors without prior information on error model is proposed.

In order to reduce the effect of NLOS error on the localization accuracy, we propose a non-parametrical NLOS localization algorithm. The proposed algorithm does not assume any statistical knowledge of the NLOS error. Without loss of generality, the proposed localization algorithm uses the TOA measurements but can easily extend to other signal features such as TDOA and RSS.

3. Problem statement

3.1. Signal model

In this section, we introduce the employed signal model in this paper. The scenario we consider is as follows: M beacon nodes are randomly placed in the field with coordinates given by $\boldsymbol{\psi}_{\mathbf{i}} = (x_i, y_i)^T$, $i = 1, \ldots, M$. The positions of obstacles are unknown. The unknown node is moving in the field, whose location at time k is $(x(k), y(k))$, $k = 1, 2, \ldots, K$. A two-dimensional analysis is provided, as extension to three-dimensions is rather straightforward.

The true distance between the ith beacon node and the unknown node at time k is

$$d^i(k) = \sqrt{(x(k) - x_i)^2 + (y(k) - y_i)^2} \tag{1}$$

In LOS propagation condition, the range measurement by the ith beacon node at time k is modeled as follows:

$$\hat{d}^i(k) = d^i(k) + n_i \tag{2}$$

where n_i is the measurement noise modeled as zero mean white Gaussian with variance σ_i^2.

In NLOS propagation conditions, the signal does not travel in a straight line when obstacle exists between the beacon node and unknown node due to the reflection or diffusion effect. So the range measurement by the ith beacon node at time k is modeled as follows:

$$\hat{d}^i(k) = d^i(k) + n_i + b_{NLOS} \tag{3}$$

where n_i is the measurement noise with zero mean and σ_i^2 variance, i.e. $N(0, \sigma_i^2)$. b_{NLOS} is the NLOS error and is assumed to be independent of the measurement noise n_i. Since the indirect propagation path is longer than the direct path, the NLOS error is assumed positive. And the NLOS error b_{NLOS} obeys Gaussian, Uniform or Exponential distribution [24]. The distribution and parameters of b_{NLOS} are different in different environments and measurement methods.

The probability density function of n_i can be described by

$$f(n_i) = \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left(-\frac{n_i^2}{2\sigma_i^2}\right) \tag{4}$$

The probability density function of b_{NLOS} when it obeys the Gaussian distribution ($b_{NLOS} \sim N(\mu_{NLOS}, \sigma_{NLOS}^2)$) is given by

$$f(b_{NLOS}) = \frac{1}{\sqrt{2\pi\sigma_{NLOS}^2}} \exp\left(-\frac{(b_{NLOS} - \mu_{NLOS})^2}{2\sigma_{NLOS}^2}\right) \tag{5}$$

The probability density function of b_{NLOS} when it obeys the Uniform distribution ($b_{NLOS} \sim U(u_{\min}, u_{\max})$) is given by

$$f(b_{NLOS}) = \begin{cases} \dfrac{1}{u_{\max} - u_{\min}}, & \text{for} \quad u_{\min} \le b_{NLOS} \le u_{\max} \\ 0, & \text{else} \end{cases} \tag{6}$$