A Non-line-of-Sight Propagation Identification Algorithm in Wireless Sensor Network

H Chu*, P Ji, S Lian, H Yang and R Wu

Faculty of Robot Science and Engineering, Northeastern University, Shenyang, Liaoning, 110000, China.

*Corresponding author’s e-mail: chuhao_neurobot@163.com

Abstract. With the rapid developing of communication technology, Wireless Sensor Network (WSN) has been applied in many fields. The accuracy of localization is the vital key to all these applications. In order to mitigate the non-line-of-sight (NLOS) influence, we propose a propagation identification algorithm based on Anderson-Darling (AD) test. Firstly, the status of signal is determined by the AD testing. Secondly, the particle swarm optimization algorithm is adopted to estimate the mobile node based on the identification results. Finally, the effectiveness of the algorithm is verified by simulation experiments.

1. Introduction

As a distributed network, Wireless Sensor Network (WSN) senses and monitors the environment. It has been widely applied in the fields of ecological monitoring, electrical automation and aerospace etc[1]. With rapid developing of communication technology, the accuracy of localization is demanding especially in the complex environment. However the non-line-of-sight (NLOS) propagation influences greatly on the localization results. Therefore, it is essential to mitigate NLOS error to improve the localization accuracy.

Many research works have been done to estimate the NLOS propagation status. A NLOS determination method based on a known propagation model is proposed to distinguish both signals in [2]. In [3], a method combining Hypothesis Test (HT) and Triangular Inequality Properties of Euclidean Space is introduced to detect whether ranging is affected by bias caused in NLOS conditions. A hybrid localization algorithm combining WTD is proposed to distinguish Line-of-sight (LOS) and NLOS paths in [4]. In [5], the Wylie algorithm is also used to identify the existence of NLOS. A Support Vector Machine (SVM) classifier is proposed to judge the signal propagation status in [6]. However, novel algorithms focusing on mobile node localization and complex environment are still in desperate need.

In this paper, we propose a NLOS propagation identification algorithm based on Anderson-Darling (AD) testing in the WSN. The proposed algorithm will detect the NLOS status with relatively low computation and the mobile node can be located with particle swarm algorithm. The rest of paper organizes as follows: in Section 2, we introduce the propagation state identification algorithm based on Anderson-Darling test; in Section 3 we perform simulation implementation and result analysis of the algorithm. And Section 4 concludes the paper.

2. Node localization algorithm based on Anderson-Darling test

2.1. Build the ranging model

There are one unknown node and N beacon nodes randomly deployed in a certain region. And the
position of the unknown node is \( \mathbf{U} = [x, y] \), the position of \( \text{ith} \) beacon node is \( \mathbf{X}_i = [x_i, y_i] \). We select Time-of-arrival (TOA) as the ranging model. Therefore, the true distance between the \( \text{ith} \) beacon node and the unknown node is:

\[
d_i = \| \mathbf{X}_i - \mathbf{U} \| 
\]

The distance measurement between unknown node and beacon node can be represented as:

\[
d̂_i = \begin{cases} 
d_i + n_i, & \text{LOS} \\
_d + n_i + n_{\text{NLOS}}, & \text{NLOS} 
\end{cases} 
\]

where \( n_i \) is the measurement noise that follows Gaussian distribution \( N(0, \sigma_i^2) \), \( n_{\text{NLOS}} \) is the NLOS error which is respective with measurement noise, \( n_{\text{NLOS}} \) follows Gaussian distribution \( N(\mu_{\text{nlos}}, \sigma_{\text{nlos}}^2) \), uniform distribution \( U(a, b) \) or exponential distribution \( E(1/\lambda) \) under different environments.

2.2. Structure of the proposed Algorithm

The flowchart of proposed algorithm is illustrated in Figure 1. When the measurement model is set up, Anderson-darling test is deployed for the NLOS propagation. If the status is LOS, the objective function is established according to the distance; else the measured value is taken as a constraint in the localization algorithm. Finally, the particle swarm optimization localization algorithm is used for positioning.

![Flowchart of the proposed algorithm](image)

**Figure 1.** The flowchart of the proposed algorithm

2.3. Propagation identification algorithm based on Anderson-darling test

Assuming that the distance between the \( \text{ith} \) beacon node and the unknown node can measure \( M \) times in a short time. The measuring distance set is presented by \( \mathbf{D}_i = [d_i^1, d_i^2, \ldots, d_i^M] \). We obtain the following assumptions:

\[
H_0: d_i^j \sim N(0, 1) 
\]

The mean and variance of the current measurement are as follows:

\[
\hat{\mu}_i = \frac{\sum_{j=1}^{M} d_i^j}{M} 
\]

\[
\hat{\sigma}_i^2 = \frac{\sum_{j=1}^{M} (d_i^j - \hat{\mu}_i)^2}{M} 
\]

The AD statistics are:

\[
AD = -\frac{1}{M} \sum_{j=1}^{M} (2j - 1) \left[ \ln z_j + \ln (1 - z_{M+1-j}) \right] - M 
\]

\[
Z_j = \phi \left( \frac{d_i^j - \hat{\mu}_i}{\hat{\sigma}_i} \right) 
\]

where \( \phi (d_i) \) represents the standard normal distribution function. Discriminant standard CV is:

\[
CV = \frac{0.752}{1 + 0.75 \times \frac{1}{M} \sum_{j=1}^{M} Z_j^2} 
\]

If \( AD > CV \), \( H_0 \) is rejected. It is considered as NLOS propagation. Otherwise, it is considered as LOS propagation.

2.4. Particle swarm optimization localization algorithm

Assuming that at least one of the measured values is line-of-sight, the mean value of the measurement
in LOS environment is \[ \bar{D}^{\text{LOS}}_1, \bar{D}^{\text{LOS}}_2, \ldots, \bar{D}^{\text{LOS}}_q \], where \( \bar{D}_i = \frac{1}{M} \sum_{j=1}^{M} \hat{d}_i^j \). The mean value of the measurement in NLOS environment is \[ \bar{D}^{\text{NLOS}}_1, \bar{D}^{\text{NLOS}}_2, \ldots, \bar{D}^{\text{NLOS}}_p \]. The location objective function is as follows:

\[
\begin{align*}
\min \quad & \sum_{i=1}^{q} \left\| \bar{d}^{\text{LOS}}_i - \sqrt{(\bar{x} - x_i)^2 + (\bar{y} - y_i)^2} \right\|
onumber \\
\text{s.t.} \quad & \sqrt{(\bar{x} - x_i)^2 + (\bar{y} - y_i)^2} \leq \bar{D}^{\text{NLOS}}_j, (j = 1, \ldots, p)
\end{align*}
\]

(2.9)

The estimated unknown node position can be obtained by solving the minimum value of the above equation. Because the formula is a nonlinear function with constraints, it is difficult to obtain the resolution directly. Therefore, particle swarm optimization localization algorithm is adopted to solve the above equation.

The parameters in the particle swarm optimization localization algorithm are defined below. The position of the particles is presented as \( S = \{ P_1, \ldots, P_L \} \), where \( L \) is the number of particles. For the \( i \)-th particle in step \( k \), the updated equation for speed and position is as follows:

\[
\begin{align*}
v_i(k) &= \omega v_i(k-1) + c_1 \xi (pbest_i - P_i(k-1)) + c_2 \eta (gbest - P_i(k-1)) \\
P_i(k) &= P_i(k-1) + v_i(k)
\end{align*}
\]

(2.10)

(2.11)

where \( v_i(k) \) and \( P_i(k) \) are the speed and position of the \( i \)-th particle at the \( k \) step, \( pbest_i \) represents the historical optimal position of the \( i \)-th particle search, \( gbest \) represents the historical optimal position of all particles search. \( c_1 \) and \( c_2 \) particle acceleration is constant. In this paper, we set \( c_1 = c_2 = 2 \). \( \xi \) and \( \eta \) are two random numbers in the range \([0,1]\), and the maximum number of iterations is 60.

3. Simulation results

3.1. Simulation environment and experimental evaluation

This section mainly evaluates the success rate and localization accuracy of NLOS. The simulation environment is as follows: \( N \) beacon nodes are deployed randomly in a square area of 60m\( \times \)60m, and the parameters of the node measurement model are shown in the Table 1.

| Parameter                        | Symbol | Default |
|----------------------------------|--------|---------|
| Number of beacon nodes           | \( N \) | 7       |
| Measurement noise standard deviation | \( \sigma \) | 1       |
| Exponential distribution NLOS error | \( E(1/\lambda) \) | \( E(1/4) \) |
| The number of measurements       | \( M \) | 500     |
| The level of significance        | \( \alpha \) | 0.05    |
| The number of units              | \( r \) | 7       |
| The number of particles          | \( L \) | 15      |

We compare the proposed algorithm with Maximum Likelihood (ML) and Residual Weighting Algorithm (Rwgh). And the average localization error is deployed to evaluate the accuracy of the localization algorithm:

\[
AVE = \frac{1}{MC} \sum_{i=1}^{MC} \left\| \bar{D}_i - U_i \right\|^2
\]

(3.1)

where \( U_i \) is the real location of the unknown node in the \( i \)-th experiment, and \( \bar{U}_i \) is the estimated location of the unknown node in the \( i \)-th experiment.

3.2. Simulation results and analysis

Figure 2 shows the relationship between the success rate of the NLOS identification algorithm and parameters \( \lambda \) when the NLOS error follows exponential distribution \( (\eta_{\text{NLOS}} \sim E(1/\lambda)) \). The successful identification rate decreases as the parameter \( \lambda \) increases. When the NLOS error follows the exponential distribution, the success rate of the NLOS identification algorithm is above 93%. Moreover,
it also indicates that the proposed algorithm can work robustly in complex environments.

Figure 3 shows the relationship between the measured noise standard deviation $\sigma_i$ and the mean localization error when the NLOS error follows the exponential distribution $E(1/4)$ and $E(1/8)$. The experiments show that the proposed algorithm improves the localization accuracy by 83.89% and 63.62% compared with the ML and R\textsuperscript{wgh} algorithms.

Figure 2. Relationship between parameter $b$ and test success rate.

Figure 3. Relationship between measurement noise standard deviation and mean localization error

4. Conclusion
This paper proposes an NLOS propagation identification method based on Anderson-Darling test. Firstly, through multiple sets of distance measurement values, statistical analysis is used to determine the signal propagation state, and then based on the determination results, a particle swarm optimization algorithm is used for positioning. Finally, the proposed algorithm is simulated. Simulation results show that the proposed algorithm can effectively suppress NLOS errors of many different distributions.

Acknowledgments
This work was supported in part by the Fundamental Research Fund for the Central Universities of China N172604004, N182613001, N172604003 and N172603001; the National Natural Science Foundation of China under Grant nos. 61901098, 61701101, 61803077, 61603080, and the National Key Robot Project under Grant nos. 2017YFB1301103.

Reference
[1] Li, H. (2013) Study of wireless sensor network applications in network optimization. Sens Transducers, 157:180–189.
[2] Venkatesh, S., Buehrer, R. (2007) Non-line-of-sight identification in ultra-wideband systems based on received signal statistics. Microwaves, IET Microwaves, Antennas and Propagation, 1:1120-1130.
[3] Destino, G., Macagnano, D., de Abreu, G.T.F. (2008) Hypothesis testing and iterative WLS minimization for WSN localization under LOS/NLOS conditions. In: 41st Asilomar Conference on Signals, Systems and Computers. Pacific Grove, CA, USA. pp. 2150-2155.
[4] Zhang, L., Chen, F., Yu, Y. (2015) Research on hybrid location algorithm with high accuracy in indoor environment. In: 34th Chinese Control Conference (CCC). Hangzhou, China. pp. 8764-8767.
[5] Li, H., Deng, Z., Yu, Y. (2011) Investigation on a NLOS error mitigation algorithm for TDOA mobile location. In: IET International Conference on Communication Technology and Application. Beijing, China. pp. 839-843.
[6] Destino, G., Macagnano, D., de Abreu, G.T.F. (2008) Hypothesis testing and iterative WLS minimization for WSN localization under LOS/NLOS conditions. In: 41st Asilomar Conference on Signals, Systems and Computers. Pacific Grove, CA, USA. pp. 2150-2155.