TOA-BASED ROBUST LOCATION ALGORITHMS FOR WIRELESS CELLULAR NETWORKS

Sun Guolin  Guo Wei
(Institute of Communication and Information Engineering, UESTC, Chengdu 610054, China)

Abstract Caused by Non-Line-Of-Sight (NLOS) propagation effect, the non-symmetric contamination of measured Time Of Arrival (TOA) data leads to high inaccuracies of the conventional TOA based mobile location techniques. Robust position estimation method based on bootstrapping M-estimation and Huber estimator are proposed to mitigate the effects of NLOS propagation on the location error. Simulation results show the improvement over traditional Least-Square (LS) algorithm on location accuracy under different channel environments.

Key words Time Of Arrival (TOA); Non-Line-Of-Sight (NLOS); Huber estimator; Bootstrapping

I. Introduction

Wireless user's location has received considerable attention over the past decades. In Time Of Arrival (TOA)-based cellular wireless location systems, Non-Line-Of-Sight (NLOS) propagation is a key and difficult issue to improve the accuracy of location estimation[1]

For TOA, traditional algorithm for Mobile Station (MS) location is based on classical techniques that minimize a sum of least-square errors or Minimum Mean Square Error (MMSE) criterion[2]. Turin originally formulated the approach for computing location by minimizing the sum of squares of a nonlinear cost function[3].

Range measurements derived from the TOAs of a signal at multiple Base Stations (BSs) are corrupted by standard measurement noise and NLOS errors. Standard measurement noise is assumed to be a Gaussian random variable, while NLOS error is a random error, which subjects to different statistical distributions in different channel environments[4], such as exponential, uniform, Gaussian, and delta distributions. However, the Least-Square (LS) location algorithm loses its optimality when the underlying distribution deviates from Gaussian distribution.

In this paper, novel position estimation algorithms based on robust M-estimation are proposed, which do not require knowledge of NLOS error statistics or a time history of range measurements as in Refs.[1,5,6]. In addition, there is no requirement to compute scale factors relative to NLOS errors, or to identify NLOS BSs heuristically as in Refs.[5,7,8].

II. Robust M-estimators for Positioning

Here, we consider that range measurements $r_m$ based on TOA received by base station $i$ is modeled as[1]:

$$r_m = L_m + n_m + \text{NLOS}_m$$ (1)

1Manuscript received date: September 15, 2003; revised date: May 8, 2004.
Communication author: Sun Guolin, born in 1978, male, Ph.D. candidate. National Key Lab. of Communication, UESTC, Chengdu 610054, China. uestcsgl@hotmail.com
where \( L_m \) is true distance between MS and the \( m \)-th BS, \( \eta_m \) is a zero mean Gaussian random variable representing standard measurement error with variance \( \delta \), \( NLOS_m \) is a random variable representing the error due to NLOS propagation, whose statistical distribution is unknown.

We assume that the MS, located at \((x, y)\), transmits a waveform at time \( \tau_0 \) with the speed of light \( c \), and the \( N \) BS receivers, located at coordinates \((x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)\), receive the waveform at times \( \tau_1, \tau_2, \ldots, \tau_N \). Our objective function is

\[
\min \sum_{m=1}^{N} \rho(e_m / \sigma_m)
\]

where \( e_m = r_m - L_m = c(\tau_m - \tau_0) - \sqrt{(x_m - x)^2 + (y_m - y)^2} \), \( \sigma_m \) is its corresponding scale, which is estimated by median absolute deviation from the median. The robust function \( \rho(r) \) and the score function \( \psi(r) = \partial \rho / \partial r \)[8] considered in this paper are given in Tab.1.

<table>
<thead>
<tr>
<th>Tab.1 Functions for position estimation ((\text{sgn}(x) = x/</th>
<th>x</th>
<th>))</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \rho(r) )</td>
<td>( \psi(r) = \partial \rho / \partial r )</td>
<td></td>
</tr>
<tr>
<td>Least-square</td>
<td>( r^2 / 2 )</td>
<td>( r )</td>
</tr>
<tr>
<td>Huber</td>
<td>( { \begin{array}{ll} r^2 / 2, &amp;</td>
<td>r</td>
</tr>
</tbody>
</table>

If \( \rho(r) \) is a convex function, an equivalent form for Eq.(2) is to find values of \((x, y)\) for which

\[
\begin{align*}
\sum_{m=1}^{N} \psi_x(e_m(x, y)) &= \sum_{m=1}^{N} \frac{\partial}{\partial x} \rho(e_m(x, y)) = 0 \\
\sum_{m=1}^{N} \psi_y(e_m(x, y)) &= \sum_{m=1}^{N} \frac{\partial}{\partial y} \rho(e_m(x, y)) = 0 
\end{align*}
\]

To robustly estimate MS location in the presence of NLOS propagation, more tolerance for outliers is required. The Huber estimator[8] is of such function and is proposed for this application.

It becomes apparent that the Huber M-estimator is capable of suppressing outliers with large amplitude. Parameter \( b \) controls the degree of suppression of the outliers. In order to provide robust estimation under NLOS environment, the choice of threshold parameters estimation plays an important role in the performance of the robust position estimator.

Although the distribution of the error \( e \) is generally unknown due to the presence of NLOS error, it is assumed to be Gaussian distributed when there is no NLOS outlier, so that[9]

\[
\theta_T(n) = \Pr\{|e(i)| > T\} = 1 - \text{erf}\left(\frac{T}{\sqrt{2} \hat{\sigma}_e}\right)
\]

where \( \text{erf}(\cdot) \) is the error function, and is defined as \( \text{erf}(r) = 2 \int_{0}^{r} e^{-x^2} dx / \sqrt{\pi} \), \( \hat{\sigma}_e^2 \) is the estimated variance, which is estimated by[10]

\[
\hat{\sigma}_e^2 = T_{\text{MAD}}(n) = 1.483 \text{median}_{i} \left( \left| e^2(i) - \text{median}_{i \neq j} (e^2(j)) \right| \right), \quad i, j = 1, 2, \ldots, N
\]