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Positioning of mobile nodes based on received signal strength and dynamic path loss

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Abstract- Mobile tracking technology is always getting better because more people want to use location services. One important part of a wireless sensor network is figuring out where something is. There are two main types of position estimate methods: target/source localization and node self-localization. Then we look into the ways for nodes to find their own locations. Signal strength, which is also called field strength, is the power output of a sender as seen by a reference receiver that is far away from the emitter. It is used in telecommunications, especially radio frequency.The Received Signal Strength (RSSI) detection method is better than others because it uses simple gear, doesn't use much power, is cheap, and so on. This makes it very useful in many situations. One of the most important factors in radio transmission for describing how fading channels spread is the path loss exponent (PLE). It is now used to solve a wide range of wireless network issues, including problems with power use, simulating the communication environment, and figuring out where something is based on the strength of the signal it receives. Because of this, PLE prediction is a great way to help with wireless networking. The focus of this paper is on positioning mobile nodes based on received signal strength and dynamic estimation of path loss exponent. To find the user's location quickly, a low-complexity late-ration algorithm is suggested, along with a low-complexity searching algorithm for dynamically estimating PLE.The Gauss-Newton method makes things even less complicated.

Keywords Location, Strength of the received signal, and Path loss exponent.

INTRODUCTION

Location-based services make it possible for many cell phone apps, like guidance, security, and social networking. So, there is a lot of interest in finding positioning techniques that are both very accurate and use very little energy. The Global Positioning System works well in open places, but it doesn't work as well when there isn't a clear line of sight, and it uses a lot of energy.

a pretty high number. Network-based tracking works well everywhere and doesn't use much power. In radio transmission, the received immediate signal power at the listener is usually thought of as the sum of large-scale path loss and small-scale fading. There is a big difference in the amount of power that is received depending on how far away the sender is from the listener. For example, to figure out where a target node is in received signal strength-based localization, you need a good PLE estimate, which is usually given by reference nodes whose places are known. To begin, if you know how dense the network is, you can guess the PLE by watching the RSS over a number of time periods and finding the mean disturbance. Since then, a lot of work has been done to predict both the area and the PLE. As the need for location-based services grows, mobile positioning technology keeps getting better. The widely used Global Positioning System (GPS) can mostly meet the needs of outdoor positioning, but it's not very good at indoor positioning because the satellite signal doesn't penetrate very well.

1. LOW COMPLEXITY ALGORITHM

2.1 Simplified Lateration algorithm

In cellular network, cellphone regularly measures RSSs and it reports upto 6 strongest RSSs from neighbor base stations. These base stations are regarded as RNs. In this paper, we suppose that there are nRNs measured by target user equipment. The ith reference node is denoted as (x_i, y_i), the target user position is denoted as (x, y). The measured RSS from the reference node RN_i is being denoted RSS_i. Therefore the relationship between RSS and the distance is expressed as in equation (1).

$$RSS_i = P_0 - 10\alpha \log_{10}(d_i) + v \qquad (1)$$

Where P_0 is the signal power at 1m distance away from RN_i, which is considered as a fixed parameter for all RN_i. Then d_i is denoted as in equation(2).

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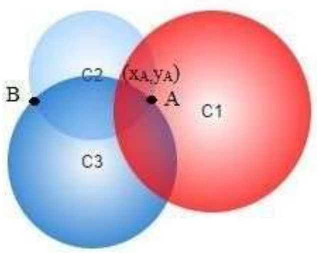
$$d_i = 10^{[p_0 - RSS_i/10\alpha]} \qquad (2)$$

when the path loss exponent is known the distance from RNs to the user's position can be calculated. The distance d_i indicates a circle C_i, denotes the possible positions of users around RN_i. A simplified lateration algorithm is proposed to estimate the users position. The signal with stronger RSS suffers less noise. Then three RNs with the strongest RSSs are chosen to apply SL, where $RSS_1 > RSS_2 > RSS_3$ respectively. Two scenarios are discussed,

SCENARIO I

Three RNs with strongest RSS is taken and with its distance d_i to the mobile nodes circles are drawn as C_1, C_2 and C_3 respectively. If C_2 and C_3 intersect with each other the nearest edge with respect to C_1 is estimated as the user position (x_A, y_A).

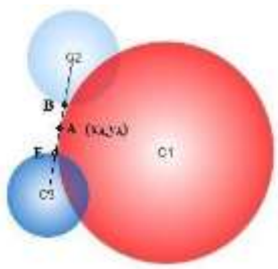


(a)

Therefore the estimated position is (x_A, y_A).

SCENARIO II

If C_2 and C_3 doesn't intersect with each other, then the midpoint between the line that connects the center's of C_2 and C_3 is estimated as the user's position (x_A, y_A).



(b)

Fig. 1. Simplified lateration algorithm with Scenario I ;(b)Scenario II.

2.2. PLE Searching algorithm

In real time environment, PLE is a unknown parameter from 2 to 6. Additionally PLE can be changed by terrain or weather. Therefore PLES is proposed to estimate PLE dynamically.In order to calculate the PLE, the difference between the distance estimated and the distance derived is required, hence it is obtained using,

PLE=mean(sqrt(sum((distanceEst-distanceDrv).^2)))

The mean square error in the target user estimation requires, mobile location and the mobile estimation datas. Therefore the positioning error is calculated as,

MSE=mean(sqrt(sum((mobileLocEst-mobileLoc).^2)))

This mean square error varies as the no of nodes and its density varies.

2.3. Gauss–Newton algorithm

The Gauss–Newton algorithm is used to solve non-linear least squares problems. It is a modification of Newton's method for finding a minimum of a function. Unlike Newton's method, the Gauss–Newton algorithm can only be used to minimize a sum of squared function values, but it has the advantage that second derivatives, which can be challenging to compute, are not required. Non-linear least squares problems arise for instance in non-linear regression, where parameters in a model are sought such that the model is in good agreement with available observations.

2. MEAN SQUARE ERROR OF DIFFERENT NODES AT DIFFERENT DENSITIES

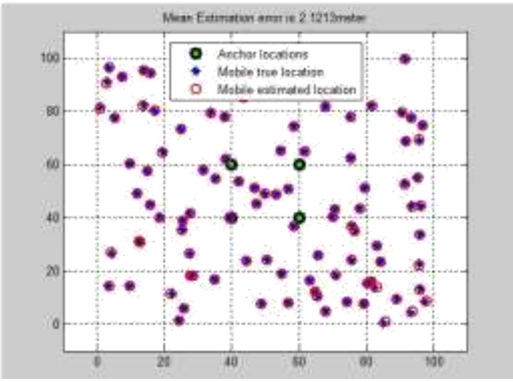


Fig. 2. Four nodes with high density.

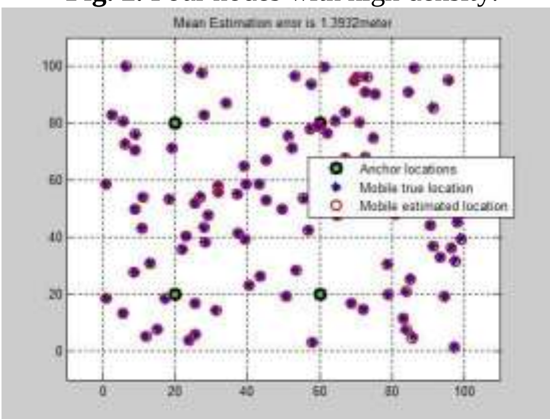


Fig. 3. Four nodes with moderate density.

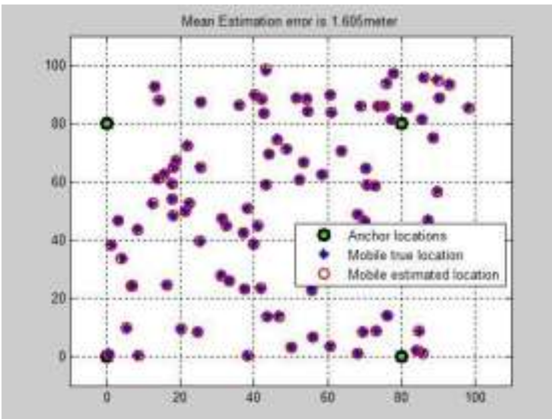


Fig. 4. Four nodes with low density.

The above Fig. 2, 3, 4 shows that four nodes with various densities like high, moderate and low.

3. SIMULATION RESULTS

An area containing three fixed RNs is considered in the simulation. The coverage of each RN is set to 800m. Initial values for NLS are randomly generated in the simulation area.

Real PLE changes randomly between 2 to 6 at every start of loop. 1000 users' positions are randomly generated in simulation area. Accuracy of PLES is about 50m worse than NLS. Reason is SL algorithm have worse accuracy than ML estimator. PLES algorithm has only about 1/30 complexity when 3 RNs are available, where the I is number of iteration which is set to 300 in consideration of both convergence and complexity. When the number of available RNs increase, this ratio decreases to 1/40.

4.1. Tabulation denoting MSE

Number of Anchor nodes(N)	Number of mobile nodes(M)	Network size	Number of Iteration	Density	Mean square error
3	1000	800	300	high	3422.851m
				moderate	3777.233m
				low	786.099m
4	1000	800	300	high	2827.600m
				moderate	927.840m
				low	411.330m
5	1000	800	300	high	1501.889m
				moderate	318.377m
				low	336.521m
6	1000	800	300	high	823.427m
				moderate	2062.011m
				low	307.408m

Table. 1. MSE for various Nodes.

4.2 . Plots for various densities

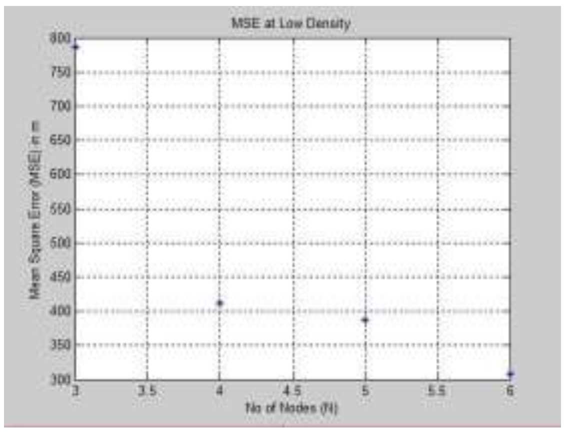


Fig. 5. Low density.

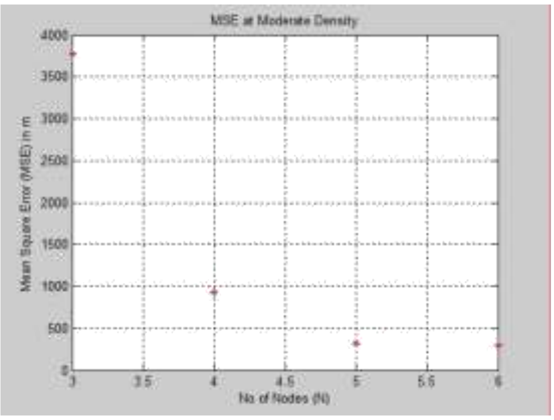


Fig. 6. Moderate density.

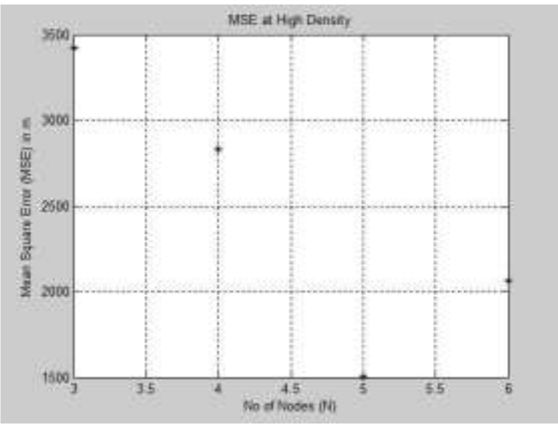


Fig. 7. High density.

Plots for various nodes with various densities denotes that, as the no of nodes increases, the MSE is decreased, these were shown in the above Fig. 5, 6, 7.

4.3 Complexity Comparison table

Algorithm M	N=3	N=4	N=5	N=6
NLS	45300	67500	95100	128100
PLES	1559	2079	2599	3119
Gauss-Newton	786	927	1430	2062

4.4 Complexity Comparison

In addition to the estimation of mobile nodes with various densities, the no of iterations when compared to classic NLS is reduced in Gauss-Newton, where the complexity is reduced. The **Fig. 8.** Shows that Complexity Comparison of various algorithms.

4.5 Plot for Complexity comparison

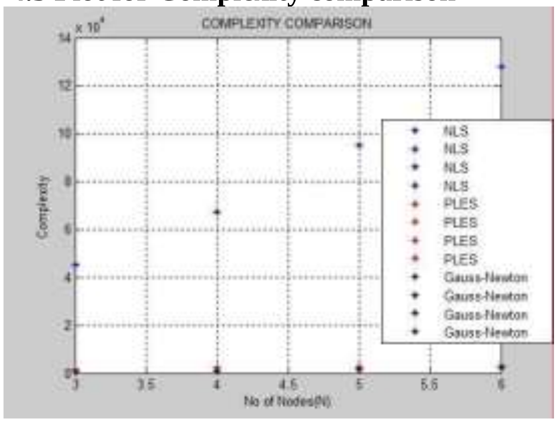


Fig. 8. Complexity Comparison.

4. CONCLUSION

The goal of this study on Received Signal Strength-based Positioning of Mobile Nodes with Dynamic Path Loss Exponent is to figure out where the user is by using simple methods like lateration, searching, and Gauss-Newton. The MSE (Mean Square Error) of different nodes with different sizes is shown on a graph. For each node, a table is made that compares how much complexity is lost in different methods. Estimating mobile nodes in NLS is easier with PLES, and even easier with the Gauss-Newton method for different nodes. This is a necessary job for tracking, military search and rescue, and guidance. So, figuring out who the target person is is easier than with the NLS and PLES algorithms. As the mistake in guessing who the person is goes down, accuracy goes up. In future work, a different method will be used to look into how to improve accuracy.

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