Modeling and Understanding the Localization Performance With Network Signatures

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ABSTRACT With the continuous development of wireless network technology, more and more mobile devices are connected to the network, and the location information of these devices is becoming one of the important bases for analyzing other geographic data in the net. Location is an important problem in spatial information sensing, and the theoretical basis of location is the free space fading feature of wireless signals. In this paper, we propose WiLocWare, which is a middle ware to understand and modeling the performance of the state-of-the-art and to be proposed algorithms. We evaluated and characterized the correlation between localization accuracy and networks parameters such as signal propagation model, the coverage of wireless radios, the distributions of wireless devices and the density of the anchor nodes. The experimental results show the localization accuracies under different wireless signatures, WiLocWare is also scalable for the performance evaluation for the to be proposed algorithms.

INDEX TERMS Localization performance, scalability, localization accuracy, wireless measurements.

I. INTRODUCTION

With the continuous development of wireless network technologies, nearly six hundred and fifty million mobile devices added in networks according to the forecast by Cisco [1]. The location information of these devices is becoming one of the important information for analyzing geographic data in both indoor [2] and outdoor [3] scenarios. The accurate location information could enable variety of applications such as pedestrian trajectory prediction [4], human behavior prediction [5], navigation systems [6], group recommendation [7] and other IoT-based applications [8]. Therefore, modeling and understanding the localization performance in different scenarios is significant for proposing accurate localization algorithms.

The location estimation methods can be classified into target/source method and node self-localization method. The target/source localization algorithms are mainly energy-based methods, while self-localization methods could enable node estimate its own location by wireless signatures such as received signal strength (RSS), channel state information (CSI), hops, topologies, radio coverages and other readable networks signatures.

However, it is hard to get the detailed correlations between localization performances with different network signatures and settings. The performance comparisons among different algorithms are also hard since the diversity of evaluation platforms and settings. Therefore, localization performance evaluation in wireless network have several challenges: i) The evaluation model should be scalable since the rapid development of location algorithm, the input parameters of different location algorithm is slightly different, leading to different performance of the location algorithm is also different. Therefore, the model should improve the scalability of the input parameters, algorithms and the evaluation index of the algorithm; ii) Traditional range-free location algorithms don’t take the influence of free space fading characteristics into account on the performance of the algorithm, and the scalability evaluation model should focus on the evaluation and iii) In addition to the fading characteristics of free space, location algorithm is also affected by other parameters of node distribution, the density of anchor node,
the communication radius of node, in the process of model design it should give full consideration and evaluation on the effects of these factors on different location algorithm.

In order to solve these three challenges, the main contributions WiLocWare proposed in this paper are as follows:

- The scalable location system is divided into four scalable modules, which are node deployment module, topology module, location algorithm module and performance evaluation module.
- In order to reduce the coupling of the four modules, three data structures are designed for scalable architecture, they are coordinate data structure, neighbor relational data structure and localization result data structure respectively. The three data structures could reduce the coupling degree of four the modules, which could improve the scalability of the middleware.
- We evaluated WiLocWare with Matlab, four kinds of deployment methods, four kinds of signal propagation methods, four classical localization algorithms were implemented to test the scalability and reliability of WiLocWare, and three kinds of performance matrix were test under WiLocWare. The simulation and experimental results show the scalability and reliability of WiLocWare.

The remainder of this paper is organized as follows, Section II introduce related works, Section III describe the WiLocWare model, and Section IV shows the evaluation results and Section V concludes the paper.

II. RELATED WORKS

Currently, there are many localization algorithms using network signatures especially in wireless sensor networks, such as the approaches proposed in paper [9]–[12]. However, the uniform middleware for the performance evaluation of localization algorithms are rare. Different research team use relatively independent platform with different parameters to evaluate the performance of localization algorithms. The diversity evaluation methods make other researchers unable to quantify the performance of base-lines with the change of parameters. In the practice application process, it is also difficult to choose the appropriate algorithm according to the actual parameters. In order to reduce the coupling of the four modules, which are node deployment module, free space fading module, location algorithm adding module and performance analysis module. The main data structures of WiLocWare model are coordinate information data structure (Coordinates.mat in Figure 1), neighbor information data structure (neighbor.mat in Figure 1) and results structure (Results.mat in Figure 1). The relationships among the four modules and the three data structures are shown in Table 2.

III. DESIGN

This section introduces the model and overall structure of WiLocWare for modeling and understanding localization performance evaluation, including scalable structure model design, node deployment model design, signal propagation model design and localization performance evaluation model design. The overall structure is shown as Figure 1.

In order to increase the scalability of WiLocWare, we separate the data and the operations according to the input parameters of localization algorithms.

The WiLocWare model consists of four sub-modules, which are node deployment module, free space fading module, location algorithm adding module and performance analysis module. The main data structures of WiLocWare model are coordinate information data structure (Coordinates.mat in Figure 1), neighbor information data structure (neighbor.mat in Figure 1) and results structure (Results.mat in Figure 1). The relationships among the four modules and the three data structures are shown in Table 2.
TABLE 1. Diversity of the localization performance platforms and settings (some examples).

| key References | Platforms          | ND    | AH | ANR | AP   | GPS error | Deployment     |
|----------------|--------------------|-------|----|-----|------|-----------|----------------|
| [13]           | Matlab Simulator   | 250/100*1000m | –  | 1   | –    | –         | randomly deployed |
| [14]           | Matlab Simulator   | 250/500*500m  | –  | 450/50 | (8,26)/2500 | –         | randomly deployed |
| [15]           | MICA2 motes        | –     | –  | –   | 10/100 | Uniform Deployed |
| [16]           | Matlab Simulator   | 110/100*100m  | –  | 1   | 10/100 | no         | Uniform Deployed  |
| [17]           | Matlab Simulator   | 85/60*50     | –  | –   | 4/81  | –         | Uniform Deployed  |
| [18]           | Matlab Simulator   | changed     | Changed | Changed | Changed | Changed | Changed     |

TABLE 2. Relationships among modules and data structures in WiLocWare.

| Data Structure       | Relationship between model and data structure |
|----------------------|-----------------------------------------------|
| data structure       | Node deployment model  | Free space fading model | Location algorithm model | Performance analysis model |
| Coordinates.mat      | Output                        | Input                       | –                       | –                       |
| Neighbor.mat         | –                             | Output                      | Input                    | –                       |
| Result.mat           | –                             | –                           | Output                   | Input                   |

The scalability of WiLocWare model can be summarized as follows:

- Researchers could add or change the node deployment module in a scalable way without modifying other modules.
- Researchers could add or change the signal propagation module in a scalable way without modifying any other modules by changing the “free space fading model”.
- Researchers could add the developed new algorithms under different deployments and signal propagation models in “location aware algorithm model”.
- Researchers could use the existing performance matrix or design new performance matrix and add them to “performance analysis module” without any changing of other modules and data structures.

A. NODE DEPLOYMENT MODEL

The parameters of nodes deployments could be summarized as Table 3.

In order to implement the scalable localization middleware, this section implements four kinds of deployments which is shown as Figure 2. Figure 2(a) shows an example of random distribution in a square area assumes GPS error are 0, Figure 2(b) shows an example of random distribution in a “C” shape area, Figure 2(c) shows an regular distribution in a square shape area, and Figure 2(d) shows an regular distribution in a “C” shape area. Other parameter are shown in Table 4.

As shown in table 4, the node density and anchor node ratio of the four distributions are the same (the error is not more than 0.1%), and the communication radius is the same (10m), assuming that the error rate of GPS is 0.

As shown in table 4, the node density and anchor node ratio of the four distributions are the same (the error is not more than 0.1%), and the communication radius is the same (10m), assuming that the error rate of GPS is 0.

Generally, GPS has errors which results in the localization error rate when nodes using anchors to estimate their locations. Figure 3 shows two deployment examples when GPS error rate is 0.1. While, Figure 3(a) is an example of random distribution in square shape area and Figure 3(b) is an example of Regular distribution in square shape area.

B. SIGNAL PROPAGATION MODEL

The free space fading model mainly refers to the signal strength varies with the distance between the transmitter
and receiver. The free space fading feature is an important theoretical basis for location and also an important factor that affecting the accuracy of location algorithms. In fact, the fading of the signal is also related to the actual deployment. This section implements four free space fading models, they are DOI model, Regular model, Logarithmic Attenuation model and RIM model. The definitions of each model are shown as follows.

1) REGULAR MODEL
Regular model assumes that the propagation range of the signal is a circular, and the received signal strength (RSS) varies with distance between sender and receiver. The RSS is calculated by Equation 1, in which the $P_t$ is the transmission energy, $PL_{d_0}$ is the reference path loss when the distance between sender and receiver is $d_0$, and $\eta$ is the constant of the channel loss. Figure 4 as shown in Equation 1. Among them, is the transmit energy; is the reference path loss when the distance between the transmitter and receiver is, and is the channel loss constant. Figure 4(a) is an example of Regular Model.

$$RSS(d) = P_t - PL_{d_0} - 10\eta \log_{10}(\frac{d}{d_0}) \quad (1)$$

2) DOI MODEL (DEGREE OF IRREGULARITY MODEL)
The DOI model introduces irregular characteristics of signals on the basis of Regular Model, and the irregular feature is defined as the maximum fluctuation in the range of the propagation direction of the wireless signal. In DOI model, the received signal strength is calculated by Equation 2. DOI is the irregular degree feature value which set by the user according to the network. Figure 4(b) is an example of wireless signal path loss when DOI= 0.01.

$$RSS(d) = P_t - PL_{d_0} - 10\eta \log_{10}(\frac{d}{d_0}) * K_i + X_e \quad (2)$$

3) RIM MODEL (RADIO IRREGULARITY MODEL)
RIM model introduces a random variable of on the basis of DOI model, which is the propagation loss of wireless signal with the uncertainty of temperature, humidity and so on. So, in the RIM model, the received signal strength is calculated by Equation 3. Figure 4(c) is an example of the RIM model (DOI= 0.01).

$$RSS(d) = P_t - PL_{d_0} - 10\eta \log_{10}(\frac{d}{d_0}) * K_i + X_e \quad (3)$$

4) LOGARITHMIC ATTENUATION MODEL
Logarithmic Attenuation model is a special case of RIM model. It does not take into account the irregular characteristics of signals, only considers the propagation losses caused by temperature and humidity of the wireless signals. The calculation method is shown as Equation 4. Figure 4(d) is an example of logarithmic attenuation model.

$$RSS(d) = P_t - PL_{d_0} + \frac{10\eta}{d_0} * X_e \quad (4)$$
example of Logarithmic attenuation model.

\[
\text{RSS}(d) = P_t - PL_{do} - 10\eta\log_{10}\left(\frac{d}{d_0}\right) + X_e
\] (4)

In summary, users could choose the wireless signal attenuation model according to the actual network deployment, and also could develop new attenuation model that matches the actual network in real-world applications.

C. PERFORMANCE INDEX MODEL

The performance matrix of localization algorithm in this paper includes location error rate, location cover rate, and energy consumption. Their specific definitions are as follows.

1) LOCALIZATION ERROR RATE

Location error rate is the difference between the estimated coordinates and the actual coordinates of the node \( i \), which is calculated by Equation 5. \( N \) represents the total number of unknown nodes, \( L(N) \) is the number of nodes that can be located by localization algorithm, \( R \) is the communication radius of the unknown node, \((x_{ie}, y_{ie})\) is the actual coordinates of the unknown nodes, \((x_{it}, y_{it})\) is the coordinates estimated by the localization algorithm.

\[
\text{error rate} = \frac{\sum_{i\in N} \sqrt{(x_{ie} - x_{it})^2 + (y_{ie} - y_{it})^2}}{L(N) \times R}
\] (5)

2) LOCATION COVER RATE

Localization cover rate of location algorithms is the ratio of the number of nodes that can be located by localization algorithm and the total number of nodes to be located, it is calculated by Equation 6.

\[
\text{cover rate} = \frac{L(N)}{N}
\] (6)

3) LOCATION ENERGY CONSUMPTION

Energy consumption is another important performance for evaluating localization algorithms. However, the energy consumption of location algorithms varies greatly with the experimental platform and devices. Therefore, the WiLocWare model proposed uses the execution time of the location algorithm in the Matlab simulator to measure the energy consumptions of localization algorithms.

IV. SIMULATION AND EVALUATIONS

In order to evaluate the localization performance of different algorithms under different platforms and settings of network signatures. We take the traditional DV-Hop algorithm, Amorphous algorithm, Centroid algorithm and APIT algorithm as examples to evaluate the scalability and reliability of WiLocWare. We evaluated the correlations between localization performances including localization error rate, localization cover rate and energy consumptions with different free space fading model, different node deployment methods, different node communication radius, different density of the anchor nodes.

A. CORRELATIONS BETWEEN LOCALIZATION PERFORMANCE AND SIGNAL PROPAGATION FEATURES

In order to investigate the correlations between localization performance and free space fading model, we deploy the nodes as Figure 2(a) with parameters shown in Table 5. The experimental results are shown in Figure 5, Figure 6 and Figure 7.

Figure 5 shows that the localization error rate of DV-Hop algorithm, Amorphous algorithm and Centroid algorithm don’t change severely with fading model; APIT algorithm is greatly affected by the fading model, the localization error rate of APIT algorithm is minimum when using Regular Model, in LA (Logarithmic Attenuation) model, the APIT algorithm has large error. However, under the same conditions, the localization error rate of the APIT algorithm is significantly lower than the other three algorithms.

![Figure 5. The influence of different fading models on the localization error rate for different algorithms.](image)

![Figure 6. The influence of different fading models on the localization cover rate for different algorithms.](image)

![Figure 7. The influence of different fading models on the running time for different localization algorithms.](image)

TABLE 5. Experimental parameter setting (influence of free space fading model).

| Parameter Name                  | Parameter Value     |
|--------------------------------|---------------------|
| Deployment                      | random distribution in square shape area |
| Deployment Area(m^2)            | 200*200             |
| The number of unknown nodes     | 105                 |
| The number of anchor nodes      | 21                  |
| Node density(number/m^2)        | 0.0032/m^2          |
| Radius of anchor nodes          | 0.17                |
| GPS error rate(%)               | 0                   |
| Communication radius(m)         | 20                  |

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Figure 6 shows that the localization cover rate of DV-Hop, Amorphous algorithm, APIT algorithm change little when we use different free space fading models. While the cover rate of Centroid algorithm when using Regular Model and DOI Model is higher than those using LA and RIM Mode.

Figure 7 shows the energy consumption (as measured by the running time) of different free fading model for localization algorithms. The energy consumption of DV-Hop algorithm, Amorphous algorithm have not significant changes with the free space fading models. The energy consumption of APIT algorithm has minor changes with the free space models. Centroid algorithm is affected by the attenuation model is large in the DOI model, and in RIM model, the energy consumption of the Centroid algorithm is larger 100 – 1000 times than the other algorithms.

B. THE CORRELATION BETWEEN LOCALIZATION PERFORMANCE AND NODE DEPLOYMENT METHODS

In order to validate the influence of node distribution on the performance of localization algorithms, we assume the free space fading model is LA Model. The parameters setting under each distribution is shown in Table 5. The parameter settings in Table 5 show that the rest of the parameters are consistent except for the different distributions. The experimental results were showed in Figure 8, Figure 9 and Figure 10 respectively. The “Square Random” label represents the random distribution in a square area (distribution in Figure 2(a), “Square Regular” represents the regular distribution in a square area (distribution in Figure 2(b), “C Random” represents the random distribution in a “C” area (distribution in Figure 2(c) ), “C Regular” represents the regular distribution in a “C” area (distribution in Figure 2(d).

Figure 8 shows the relationship between the localization error rate and node distribution for different localization algorithms, the experimental results show that the error rate of DV-Hop algorithm and Amorphous algorithm do not change a lot when we use different distributions. While the error rate of Centroid and APIT algorithm change greatly with different distributions.

Figure 9 shows the influence of different node distribution on the error rate of node location algorithm, the experimental results show that DV-Hop algorithm, Amorphous algorithm, APIT algorithm are affected by different distribution is small. But Centroid algorithm is greatly affected by the different distribution.

Figure 10 shows the energy consumptions of different localization algorithms with different distributions. The experimental results show that the energy consumption (run time in Matlab Simulation) of DV-Hop algorithm, Amorphous algorithm, Centroid algorithm do not change much with the changing of distributions, while the energy consumptions of APIT algorithm changes a lot with different distributions.

C. CORRELATIONS BETWEEN LOCALIZATION PERFORMANCE AND COMMUNICATION RADIUS

In order to investigate the correlations between communication radius and localization performance, this section tests localization error rates with different communication radius, the parameters are showed in Table 6, the distribution is random in square area, the attenuation model is LA, the number of unknown node, the number of anchor node density and anchor node proportion are shown in Table 6, in order to simulate the real-world scenarios, the GPS error rate is set to 0.06. The radius of communication varies from 20m to 210m. Where 20m is more consistent with the actual settings of node (e.g., MacZ motes and TelB nodes), 210m assumes that the communication radius is larger than the distribution area and is used to test the performance of the algorithm in the limit case.

The experimental results under the settings of Table 6 are shown in Figure 11. The localization error rate is shown in Figure 11(a), the localization cover rate is shown in Figure 11(b) and the energy consumptions are shown in Figure 11(c).

Figure 11(a) shows the localization error rate changing trend with the radius of communication. The experimental
TABLE 6. Experimental settings (communication radius varies).

| Deployment                                      | Random distribution in square shape area |
|------------------------------------------------|------------------------------------------|
| communication model                            | LA Model                                 |
| The number of unknown nodes                    | 105                                      |
| The number of anchor nodes                     | 21                                       |
| Node density (number/m²)                       | ≈0.0032 m²                              |
| Ratio of anchor nodes                          | 0.17                                     |
| GPS error rate (%)                             | 0.06                                     |
| Communication radius (m)                       | [20, 30, 40, 50, 60, 70, 80, 90, 100, 110, 120, 130, 140, 150, 160, 170, 180, 190, 200, 210] |

results show that the location error rate of different algorithms has different distribution characteristics with the change of communication radius R. In general, the change in the location error rate is roughly divided into two zones. When the communication radius $R = [20, 30, \ldots, 90]$ m, the location error rate of DV-Hop algorithm and Amorphous algorithm is larger, and the location error rate of Centroid algorithm and APIT algorithm is smaller. However, with the increasing of communication radius, the location error rate of DV-Hop algorithm and Amorphous algorithm continues to decrease, but the location error rate of Centroid algorithm and APIT algorithm will increase with the increase of communication radius.

Figure 11(b) shows the change of localization cover rate as the radius of communication varies. It can be seen from Figure 11(b) that the localization cover rate of different algorithms present different distribution characteristics with the change of communication radius $R$. When the communication radius $R < 100$ m, the location cover rate of the Centroid algorithm and the APIT algorithm increases with the increase of the communication radius. When $R > 100$ m, the location error rate of the Centroid algorithm and the APIT algorithm can reach 100%. However, when the communication radius varies from 20 m to 210 m, the location cover rate of DV-Hop algorithm and the Amorphous algorithm can reach 100%.

Figure 11(c) shows the relationship between the running time of the algorithm (energy consumption) and the radius of communication. The results in Figure 11(c) demonstrate that the energy consumptions of DV-Hop algorithm and Amorphous algorithm are minimum, and it changes with the communication radius. The energy consumptions of Centroid algorithm are slightly higher than the above two algorithms, but not changes with the communication radius. The energy consumption of APIT algorithm increases with communication radius increases.

D. INFLUENCE OF ANCHOR NODE DENSITY OF COMMUNICATION RADIUS ON ALGORITHM PERFORMANCE

In order to verify the influence of anchor node density on the performance of localization algorithm, the experimental parameters are shown in Table 7, the distribution type is random distribution in square area, communication model is
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Table 7: Experimental settings (the number of anchor nodes changes).

| Varying communication radius of node | Deployment | Random distribution in square shape area |
|--------------------------------------|------------|------------------------------------------|
| communication model                  | LA Model   |                                          |
| the number of unknown nodes          | 105        |                                          |
| Communication radius (m)             | 20         |                                          |
| GPS error rate (%)                   | 0.06       |                                          |
| the number of anchor node            | 10 20 30 40 50 60 70 80 90 100 110 120 130 140 150 160 170 180 190 200 210 220 230 240 250 260 270 280 290 300 310 320 330 340 350 360 370 380 390 400 | |

LA model, the number of unknown nodes is 105, GPS error rate is 0.06, communication radius is 20m. The number of anchor nodes is vary from 10 to 400. The anchor node density is less than 1, which meets the cost performance requirements of the network. In this section, we test the limit of increasing density of anchor nodes. The experimental results are shown in Figure 12.

Figure 12(a) shows the relationship between the localization error rate and the anchor node density. The experimental results show that when the proportion of anchor nodes and unknown nodes changes from 0.1 to 4, the location error rate of DV-Hop algorithm, Amorphous algorithm and APIT algorithm has stable fluctuation. The location error ratio of Centroid is decreased with increasing the number of anchors.

Figure 12(b) shows the relationship between localization cover rate and anchor node density. The experimental results show that when the proportion of anchor nodes and unknown nodes changes from 0.1 to 4, DV-Hop algorithm, Amorphous algorithm can achieve 100%, with the increase of the density of anchor nodes, the the cover rate of Centroid location algorithm and APIT algorithm will continue to increase, when the number of anchor nodes is 2 times of the unknown node, the location cover rate of Centroid algorithm and APIT algorithm is close to 100%.

Figure 12(c) shows the relationship between the location cover rate and anchor node density. The experimental results show that when the proportion of anchor nodes and unknown nodes changes from 0.1 to 4, the running time of the four classical location algorithms are significantly increased. The the speed of running time of DV-Hop algorithm and Amorphous algorithm increasing slowly, the running time of Centroid algorithm and APIT algorithm improves quickly.

We have the following conclusions according to the test for different localization algorithm by using WiLocWare.

- Fading model selective features of location aware algorithms
  **Conclusion 1:** different fading models have little influence on the localization error rate of DV-Hop algorithm and Amorphous algorithm, and have great influence on the localization error rate of Centroid algorithm and APIT algorithm.
  **Conclusion 2:** different fading models have no influence on the localization cover rate of DV-Hop algorithm and Amorphous algorithm, and have great influence on the cover rate of Centroid and APIT algorithms.
  **Conclusion 3:** different fading models have little influence on the running time (energy consumption) of the DV-Hop algorithm and the Amorphous algorithm, and has a greater impact on the Centroid algorithm and the APIT algorithm.

- The distribution selective characteristics of location algorithms
  **Conclusion 1:** different distributions have little influence on the DV-Hop algorithm and the Amorphous algorithm, but the localization error rates of Centroid algorithm and APIT algorithm are larger in regular distribution.
  **Conclusion 2:** different distributions have little influence on localization cover rate of DV-Hop algorithm and Amorphous algorithm. Centroid algorithm and APIT algorithm have lower cover rates in regular distribution.
Conclusion 3: different distributions have little influence on the running time (energy consumption) of DV-Hop algorithm, Amorphous algorithm and Centroid algorithm, but some distributions could help to reduce the running time (energy consumption) of APIT algorithm.

- Communication radius selectivity characteristics of localization algorithm

Conclusion 1: the localization error rate of different algorithms varies according to the communication radius. In general, the error rate is roughly divided into two ranges: when the communication radius $R = [20,30,\ldots,90]$ m, the error rate of DV-Hop algorithm and Amorphous algorithm is larger, and the localization error rate of Centroid algorithm and APIT algorithm is smaller. But with the increasing of communication radius, the error rate of DV-Hop algorithm and Amorphous algorithm continue to decrease, and the error rate of Centroid algorithm and APIT algorithm will increase with the increasing of communication radius.

Conclusion 2: the cover rate of different algorithms varies with the radius of communication. Generally speaking, when the communication radius $R > 100$ m, the coverage rate of Centroid algorithm and APIT algorithm increases with the increase of communication radius. When $R > 100$ m, the coverage rate of Centroid algorithm and APIT algorithm can reach 100%. However, when the communication radius varies from 20 m to 210 m, the cover rate of DV-Hop algorithm and Amorphous algorithm can reach 100%.

Conclusion 3: running time of different algorithms varies with the communication radius has different distribution characteristics. The energy consumption of DV-Hop algorithm and Amorphous algorithm is minimum, and not change with the communication radius. The energy consumption of Centroid algorithm is slightly higher than the above two algorithms, but also not change with the communication radius. The energy consumption of APIT algorithm increases with increasing communication radius.

- Anchor node proportion selective characteristics of localization algorithm

Conclusion 1: the localization error rate shows different characteristics with the density of anchor nodes in different algorithms. When the proportion of anchor nodes and unknown nodes changes from 0.1 to 4, the error rate of DV-Hop algorithm, Amorphous algorithm and APIT algorithm shows a steady fluctuation trend. The error rate of Centroid algorithm decreases with the increasing of anchors’ number.

Conclusion 2: the localization cover rate shows different characteristics with the density of anchor nodes in different algorithms. When the proportion of anchor nodes and unknown nodes changes from 0.1 to 4, the coverage rate of DV-Hop algorithm and Amorphous algorithm can achieve 100%. With the increase of anchor nodes density, the cover rate of Centroid location algorithm will continue to increase. When the number of anchor nodes is 2 times the number of unknown nodes, the location cover rate of Centroid algorithm and APIT algorithm approaches 100%.

Conclusion 3: different running time shows different characteristics with the density of anchor nodes. When the proportion of anchor nodes and unknown nodes changes from 0.1 to 4, the running time of the four kinds of classic algorithms are significantly increased, the running time of DV-Hop algorithm and Amorphous algorithm increases slower, the running time of Centroid algorithm, and APIT algorithm increases faster.

V. CONCLUSION

Location is an important problem in spatial information sensing, and the theoretical basis of location is the free space fading feature of wireless signals. In this paper, we propose WiLocWare which is a scalable middleware for modeling and understanding the performance of the localization algorithms with different network signatures. The main contributions of WiLocWare is the scalability, the data and operation separation design. Experimental results show that the middleware could help researchers investigate more insights of the localization algorithms.

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REFERENCES

[1] Cisco visual Networking Index (VNI) Global Mobile Data Traffic, Cisco, San Jose, CA, USA, 2019.
[2] I. E. Radoi, D. Cirimpeii, and V. Radu, “Localization systems repository: A platform for open-source localization systems and datasets,” in Proc. Int. Conf. Indoor Positioning Indoor Navigat. (IPIN), Sep. 2019, pp. 1–8.
[3] J. Wang, J. Luo, S. J. Pan, and A. Sun, “Learning-based outdoor localization exploiting crowd-labeled WiFi hotspots,” IEEE Trans. Mobile Comput., vol. 18, no. 4, pp. 896–909, Apr. 2019.
[4] Z. Chen, H. Cui, Y. Zhang, C. Wu, M. Mu, Z. Li, and M. A. Sotelo, “A novel sparse representation model for pedestrian abnormal trajectory understanding,” Expert Syst. Appl., vol. 138, Dec. 2019, Art. no. 112753.
[5] H. Sun, Z. Lu, C.-L. Chen, J. Cao, and Z. Tan, “Accurate human gesture sensing with coarse-grained RF signatures,” IEEE Access, vol. 7, pp. 81227–81245, 2019.
[6] B. Wu, T. Cheng, T. Yip, and Y. Wang, “Fuzzy logic based dynamic decision-making system for intelligent navigation strategy within inland traffic separation schemes,” Ocean Eng., vol. 197, Feb. 2020, Art. no. 106909.
[7] Z. Huang, X. Xu, H. Zhu, and M. Zhou, “An efficient group recommendation model with multi-attention-based neural networks,” IEEE Trans. Neural Netw. Learn. Syst., pp. 1–14, Jan. 2020.
[8] Z. Huang, X. Xu, J. Ni, H. Zhu, and C. Wang, “Multimodal representation learning for recommendation in Internet of Things,” IEEE Internet Things J., vol. 6, no. 6, pp. 10675–10685, Dec. 2019.
[9] J. J. Caffery, “A new approach to the geometry of TOA location,” in Proc. Veh. Technol. Conf. Fall IEEE VTC Fall VTC. 52nd Veh. Technol. Conf., vol. 4, Sep. 2000, pp. 1943–1949.
[10] T. He, C. Huang, B. M. Blum, J. A. Stankovic, and T. Abdelzaher, “Range-free localization schemes for large scale sensor networks,” in Proc. 9th Annu. Int. Conf. Mobile Comput. Netw. (MobiCom), 2003, p. 81.
[11] S. Sen, B. Radunovic, R. R. Choudhury, and T. Minka, “Spot localization using PHY layer information,” in Proc. ACM Mobisys, 2012, pp. 183–196.
[12] Z. Li, T. Braun, and D. C. Dimitrova, “A passive WiFi source localization system based on fine-grained power-based trilateration,” in Proc. IEEE 16th Int. Symp. World Wireless, Mobile Multimedia Netw. (WoWMoM), Jun. 2015, pp. 1–9.
[13] Z. Chaczko, R. Klempos, J. Nikodem, and M. Nikodem, “Methods of sensors localization in wireless sensor networks,” in Proc. 14th Annu. IEEE Int. Conf. Workshops Eng. Comput.-Based Syst. (ECBS), 2007, pp. 145–152.

[14] S. Zhang, J. Cao, Y. Zeng, Z. Li, L. Chen, and D. Chen, “On accuracy of region based localization algorithms for wireless sensor networks,” Comput. Commun., vol. 33, no. 12, pp. 1391–1403, Jul. 2010.

[15] H.-L. Chang, J.-B. Tian, T.-T. Lai, H.-H. Chu, and P. Huang, “Spinning beacons for precise indoor localization,” in Proc. 6th ACM Conf. Embedded Netw. Sensor Syst. (SenSys), 2008, p. 127.

[16] C. Li, Y. Li, Y. Shen, L. Liu, and Q. Cao, “An optimization algorithm for wireless sensor networks localization using multiplier method,” in Proc. 3rd Int. Joint Conf. Comput. Sci. Optimize., 2010, pp. 337–341.

[17] P. Singh and S. Agrawal, “Node localization in wireless sensor networks using the M5P tree and SMOreg algorithms,” in Proc. 5th Int. Conf. Comput. Intell. Commun. Netw., Sep. 2013, p. 104.

[18] T. He, C. Huang, B. M. Blum, J. A. Stankovic, and T. Abdelzaher, “Range-free localization schemes for large scale sensor networks,” in Proc. the 9th Annu. Int. Conf. Mobile Comput. Netw. (MobiCom), 2003, p. 81.

[19] D. Niculescu and B. Nath, “Localized positioning in ad hoc networks,” Ad Hoc Netw., vol. 1, nos. 2–3, pp. 247–259, Sep. 2003.

[20] R. Nagpal, H. Shrobe, and J. Bachrach, “Organizing a global coordinate system from local information on an ad hoc sensor network,” Inf. Process. Sensor Netw., pp. 333–348, Apr. 2003.

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