Research article Available online www.ijsrr.org ISSN: 2279–0543

International Journal of Scientific Research and Reviews

Fingerprint Localisation Technique for Noisy Wireless Sensor Networks

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ABSTRACT

Fingerprint localisation technology victimization received signal strength indication (RSSI) has become one among the recent spots within the analysis field of indoor positioning supported wireless device networks (WSNs) because of the presence of the activity noise of the RSSI, the load of the standardization purpose within the current fingerprint positioning formula isn't optimised. The authors propose a fingerprint localisation formula for hissing WSNs supported associate degree innovative multi-objective organic process model. The projected formula initially employs the Kalman filter to filter the abnormal RSSI price, and then utilises a noise variance calculator to understand the noise variance of the RSSI. Finally, the multi-objective evolutionary model is employed to search for the optimised weight of the standardization purpose via the filtered RSSI and therefore the perceived noise variance. That the novel evolutionary model will realize the simplest fingerprint estimate with the optimised weight has been verified in theory during this work. In depth experimental results on associate degree ready-made WSN test bed show that authors proposed algorithm improves the accuracy of the progressive fingerprint positioning formula by a minimum of five hundredth despite the location of the target node, the quantity of beacon nodes, the size of the standardization cell, and therefore the range of nearest neighbours.

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INTRODUCTION

Fingerprint localisation using radio- frequency signals in wireless networks is one among the commonly used indoor positioning technologies. Since the worldwide positioning system cannot offer localisation services within the area, the indoor positioning technique has become a hot spot of analysis. At present, the fingerprint localisation technology primarily based on received signal strength indication (RSSI) in wireless sensor networks (WSNs) is planned. The WSN could be a reasonably ad-hoc network,that consists of some nodes equipped with sensors, transceivers, and microcontrollers. In the WSN, the strength of the radio-frequency signal, particularly the RSSI, is simple to be measured by the transceiver. These measured RSSIs and therefore the corresponding measure positions represent node within the fingerprint localisation. According to whether requiring measuring the gap between nodes in the method of localisation or not, the positioning algorithmic program for the WSN is split into two categories: one is range- primarily based and therefore the different is range-free. In addition to the fingerprint localisation algorithmic program (FLA), there are some other range-based algorithms that can be applied to indoor positioning. These algorithms mainly include time of arrival, time difference of arrival, angle of arrival and so on. Though they will be used to calculate the placement of the node within the WSN, a extremely precise time synchronisation of the network is needed. In general, this demand is tough to realize for the WSN with restricted energy sources, computing power, and communication capabilities because of the RSSI-based fingerprint positioning doesn't need strict network synchronisation, it's terribly appropriate for the resource- strained WSN. In the present, fingerprint localisation is especially composed of two sections: the one is the off- line standardisation phase, and therefore the different is that the on- line positioning section. within the off- line standardisation section, the mapping relationship between the mean of measured RSSI, particularly the tag fingerprint, and therefore the measure location, particularly the standardisation purpose, is established. In the online positioning part the fingerprint within the radio map and therefore the RSSI measured by the target node settled in associate degree unknown position are matched to find one or additional adjacent standardisation points. Finally, these standardisation points and their weights are used to estimate the location of the target node. Currently, the most wide adopted FLAs are the nearest neighbour (NN) algorithm, the K-NN (KNN) algorithm, and the weighted KNN(WKNN) algorithm which are used as benchmarks for performance evaluation of different fingerprint positioning algorithms. The NN uses only one nearest standardisation purpose because the location of the target node, whereas the KNN directly uses the coordinate mean of the multiple nearest standardisation points because the calculable node position. Obviously, the KNN is more accurate than the NN. On the basis of the KNN, the WKNN assigns totally different weights to the various nearest calibration points. As a result, the node location calculable by the WKNN is usually more correct than the one calculable by the KNN. However, the calibration-point weight calculated by the WKNN isn't optimum in the noisy atmosphere. In this paper, we have a tendency to propose associate degree FLA for the reedy WSN supported associate degree innovative multi-objective evolutionary model, which optimises the load of the standardisation purpose in fingerprint localisation under the noise atmosphere. The FLA is created from three steps. First, the Kalman filter (KF) is utilized to filtrate the abnormal value of measured RSSI, so a noise variance figurer (NCE) is utilized to sense the noise variance of filtered RSSI. Finally, the multi- objective evolutionary model is employed to look optimised fingerprint estimation with the foremost matched noise variance, i.e. the fingerprint estimate corresponding to the node position estimated by the optimal weight of standardisation purpose.

1.1 Contributions

i. An innovative multi- objective evolutionary model for looking the optimum calib ration-point weight is established based on two newly-built objective functions. To the simplest of our information, this is the only evolutionary model that can be applied to optimising the calibration-point weight by now.

ii. A fingerprint localisation algorithmic rule for the noisy WSN supported the novel multi-objective evolutionary model is proposed. Our planned algorithmic rule can achieve the optimum node- location estimation based on the calibration-point weight calculated by the evolutionary model, that is strictly proved in theory in this paper.

iii. The effectiveness and also the efficiency of the proposed algorithm are verified by a large range of practical experiments under different parameter settings. Extensive experiment results show that our proposed algorithmic rule will improve the positioning accuracy of the progressive FLA by at least five hundredth despite the amount of beacon nodes, the location of the target node, the size of the standardisation cell, and also the range of NNs.

In this section, we describe the terminology relating to fingerprint positioning and formalise the objective of the optimisation problem. In general, fingerprint localisation consists of two phases, i.e. the off-line calibration phase and the online positioning phase. To ensure the FLA to achieve the high accuracy, the calibration points need to be deployed around the target node.

The radio map is composed of a set of the calibrated fingerprints at the calibration points, which is also known as the fingerprint database

1.2 Organisation

The organisational structure of this paper is shown as follows. Section 2 introduces the related work; Section 3 shows the results and analysis of experiments. Finally, Section 4 concludes the paper.

2 RELATED WORK

At present, the algorithm used for indoor filtering algorithm and thus on. The neural network algorithm is to see the mapping path of input and output through the training of the existing data. The measured RSSI are mapped to the foremost possible node location supported the established neural network graph because of the presence of the measurement noise, the fingerprint positioning algorithm using the neural network is probably going to map the noisy RSSI to the incorrect path, i.e. produce inaccurate node position estimation. On the opposite hand, the accuracy of derived neural network conjointly depends on the position of the target and also the range of the anchors. The study shows that the performance of the neural network-based algorithm is healthier than that of the KF-based algorithm. However,the test bed within the experiment is just too little to totally measure the performance of the neural network.

A more realistic study in reveals the above limitations of the neural network, therefore it will be seen this algorithm is not appropriate for fingerprint localisation in the main contains the neural network algorithm, the machine learning algorithm, the pattern matching algorithm, the Kalman fingerprint localisation within the noise surroundings. The machine learning algorithm is to dig out helpful info from a large quantity of knowledge thus on establish the connection between things. According to the knowledge obtained by mining, the measured RSSI can be allotted to the corresponding fingerprint classification. The coordinates of the standardization purpose during this fingerprint classification are used because the calculable node position. Just like the neural network algorithm, the noisy RSSI is feasible to create the fastened classification relationship established by the machine learning algorithm supported historical knowledge invalid. Totally different machine learning algorithms for indoor positioning are compared in terms of accuracy and interval. The results show that the machine learning-based algorithms are complicated in implementation and need high memory and computation demand. In contrast, the pattern matching algorithm, like the WKNN, is always economical to pick out the standardization points most close to the target node. Although the WKNN algorithm can be used for noisy fingerprint positioning, its node location estimate is not best within the noise environment. in the present, some algorithms are planned to improve the localisation accuracy of the WKNN. These algorithms mainly are divided into two classes: the one is to change the quantity of selected NNs within the WKNN, and also the other is to redefine the weight calculation for the standardization purpose. Since the range of NNs plays very little role on the estimation results of the node position, the development impact of the previous rule on the positioning precision of the WKNN is very limited. Despite that the latter algorithm tries to extend the localisation accuracy of the WKNN by redefining the formula of the weight, it doesn't set up the evolutionary model for optimising the burden.

3 PERFORMANCE EVALUATION

In this section, we conduct extensive practical experiments to evaluate the performance of the proposed algorithm based on a WSN testbed made up of off- the-shelf MicaZ motes under different number of beacon nodes, different location of target node, different size of calibration cell, and different number of NNs.

3.1 Experiment setup

In the experiment, 20 target nodes are randomly deployed in 100 different locations of an area of 10 m × 10 m, respectively, and 4 beacon nodes are placed around this square area, as shown in Fig. 4. The beacon node transmits the signal at one time per second, and the target node measures the RSSI of the signal transmitted by the beacon node. To ensure that the cells at which the calibration points are located cover all the positions of target nodes, the entire WSN deployment region is partitioned into 25 cells with the edge length of 2 m. Since the MOEA does not require knowing the exact location guess of the target node, the calibration points in all the cells are used to search the optimal location estimate of the node.

Fig. 1 Experiment scenario

The parameter P_X for the FLA obeys a standard normal distribution with the standard deviation of 1.The state transfer function and the measurement function used in the KF are represented by the unit matrix with same dimension, where the dimension is equal to the number of beacon nodes. Since the nodes that transmit and receive signals are static, the process noise covariance for the KF is diag(0,…,0).

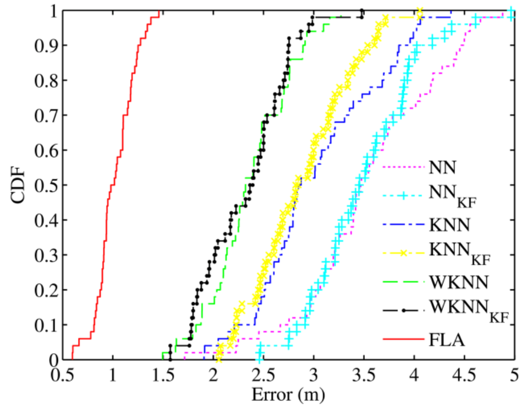

Fig. 2 RMSE CDFs of NN, KNN, WKNN, NN$_{KF}$, KNN$_{KF}$, WKNN$_{KF}$ and FLA after positioning the 20 target nodes separately placed at 100 different locations

The initial measurement noise covariance and the initial state estimation error covariance of the KF are often set empirically, so they are diag(3,…,3) and diag(1,…,1) in this paper, respectively. In each experiment, the target nodes sample 100 RSSI measurements of the beacon nodes, respectively, i.e. the number of time steps for the KF is 100.

3.2 Impact of Node Placement

In this subsection, by changing the position of the target node, we observe the effect of the placement of the target node on the localisation accuracy of the algorithm. The 20 target nodes are placed in 100 randomly selected locations, respectively. Fig. 5 exhibits the cumulative distribution functions (CDFs) of the errors generated by the NN, KNN, WKNN, NN$_{KF}$, KNN$_{KF}$, WKNN$_{KF}$ and FLA algorithms after positioning the target nodes in different locations. To compare the accuracy improvement of the KF on fingerprint localisation, the algorithms that use the original RSSI, namely NN, KNN and WKNN, and the algorithms that use the filtered RSSI, namely NN$_{KF}$, KNN$_{KF}$ and WKNN$_{KF}$, are evaluated, respectively. As is observed from the figure, the placement of the target node has a great influence on the positioning results of NN, KNN and WKNN regardless of the use of original RSSI or filtered RSSI. Since the weights that the KNN and the WKNN use are non- optimised, even their errors are sometimes more than that of NN. However, the different placed positions of target nodes have very little influence on the localisation results of FLA. This is mainly because it has an optimised weight of fingerprint estimate and position estimate. Hence, no matter how the target nodes are placed, the FLA always maintains a higher and more stable positioning precision compared to the other algorithms.

Fig. 6 shows the average RMSE of each algorithm to estimate the positions of 20 target nodes with different locations. Due to the placement positions of target nodes are randomly selected, the obtained average RMSE can reflect the positioning accuracy of the algorithm on the whole. Can be seen from the figure, the error of WKNN giving different weights to calibration points is smaller than those of NN and KNN. Although the WKNN considered the weight, the calculation of the weight is relatively simple and not optimal compared with the FLA. Due to the limited filtering ability of KF on the measurement noise of RSSI, the filtered RSSI has a very small effect on improving the accuracy of the NN, KNN and WKNN algorithms. For NN, KNN, WKNN, NN_{KF}, KNN_{KF} and $WKNN_{KF}$, the FLA reduces their errors by 71, 66, 56, 70, 64 and 55%, respectively.

3.3 Impact of the number of beacon nodes

To compare the influence of the number of beacon nodes on the localisation accuracy of the algorithm, we increase the number of beacons from 4 to 8, as shown in Fig. 4. At the same time, in order that the influence of the placement of the beacon node on the algorithm is observed, some beacon nodes are not symmetrically placed. In addition, in order to verify the performance of the proposed algorithm, we randomly select 100 locations in the WSN deployment area to place 20 target nodes in turn. For each number, of beacon nodes, the experiment is repeated 100 times, and the average error of all position estimates is used to measure the positioning accuracy of the algorithm.

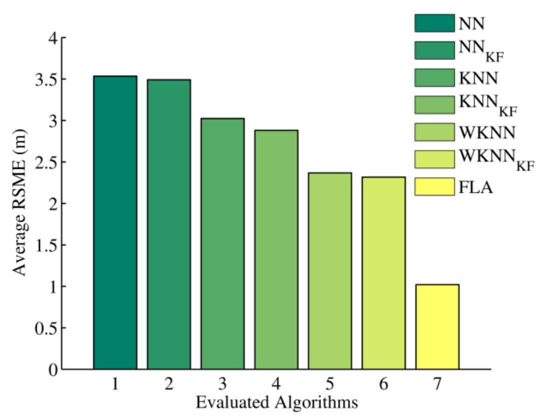

Fig. 3 Average RMSEs of NN, KNN, WKNN, NN_{KF}, KNN_{KF}, $WKNN_{KF}$ and FLA positioning the 20 target nodes separately placed at 100 randomly selected locations

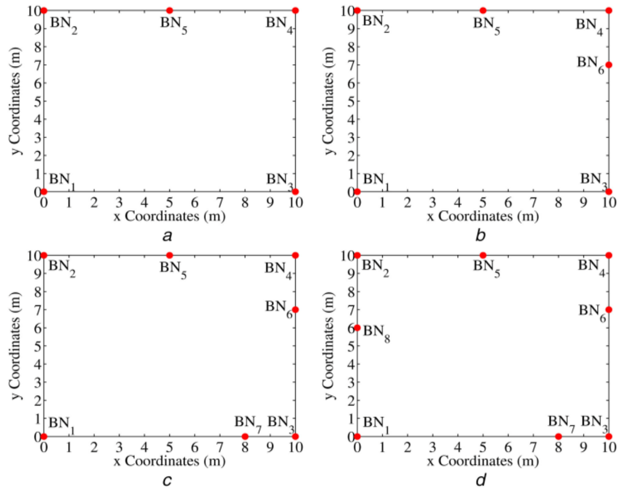

Fig. 4 Different number of beacon nodes

Fig. 3 presents the variation of the localisation accuracy of the algorithm under a different number of beacon nodes. Can be found from the figure, when the beacon node is not symmetrically added, i.e. when the number of beacon nodes is separately equal to 5, 6 and 7, the positioning error of the algorithm is not reduced.

The corresponding algorithm is named WKNN1, WKNN2, WKNN3 and WKNN4. Fig. 10 reveals the average error of all the experimental results obtained under different number of nearest fingerprints. Can be observed from the figure, when the nearest fingerprint number is increased from 3 to 4, the errors of the KNN, WKNN1, WKNN2, WKNN3 and WKNN4 algorithms do not reduce, but slightly grow. This is primarily attributed to that the weight calculated based on the distance between noisy fingerprints is not optimal in the noise environment. In contrast, the weight evolved by the FLA is optimal under the noisy environment.

As a result, no matter how the number of NNs and the weight factor change the positioning accuracy of the FLA is always much higher than those of the other algorithms.

3.4 Computational Complexity Analysis

The time complexities of all the algorithms are evaluated based on the MATLAB that runs on a computer equipped with a CPU of 2.20 GHz. The average execution time of the NN, KNN and WKNN algorithms is calculated according to the results obtained from all the experiments, which is 7.8, 7.9 and 8.3 ms, respectively.

The running time per time step of the KF in the FLA is 0.9 ms, where the maximum running time of the time step is 1.2 ms.

The average execution time of each generation of the MOEA in the FLA is 43.9 ms, and the worst execution time of the generation is 48.2 ms. For the FLA, the optimal weight can be found through the evolution of only 20 generations.

In most practical applications of WSN positioning, the signal transmission cycle of the node is greater than 1 s in general. Therefore, our proposed algorithm can meet the real-time requirements of these applications.

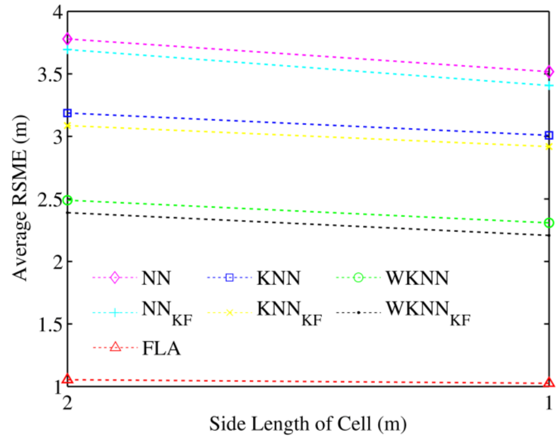

Fig. 5 Average RMSEs of NN, KNN, WKNN, NN_{KF}, KNN_{KF}, $WKNN_{KF}$ and FLA under different size of calibration cell

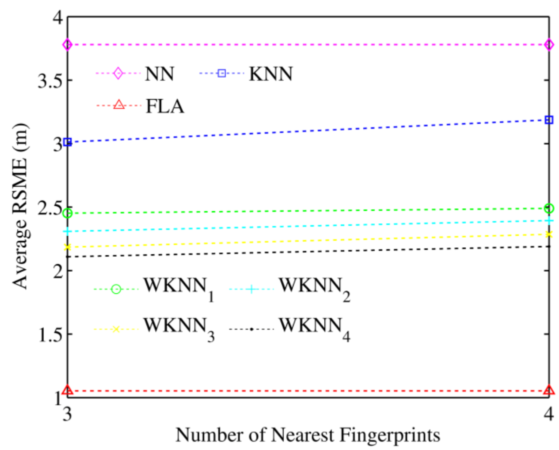

Fig. 6 Average RMSEs of the NN, KNN, $WKNN_1$, $WKNN_2$, $WKNN_3$, $WKNN_4$ and FLA under different number of nearest fingerprints

4 CONCLUSION

To improve the accuracy of the existing FLA in noisy environment, we optimised the calibration-point weight of the fingerprint positioning algorithm based on an innovative multi-objective evolutionary model. This novel evolutionary model is applied in our proposed FLA for noisy WSNs. The node location mapped by the fingerprint estimated via the optimised weight is optimal, which has been proven in theory in this paper. In addition, we also conducted a large number of practical experiments to verify the effectiveness and the efficiency of the proposed algorithm in different beacon nodes, different target positions, different cell sizes and different NNs. Extensive experiment results show that our proposed algorithm improved the positioning accuracy of the current FLA by at least 50% regardless of the number of beacon nodes, the placement of the target node, the size of the calibration cell and the number of NNs.

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