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Full Length Research Paper

Research on indoor positioning algorithm based on powerline

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In this research, the basic principle of data acquisition based on powerline is introduced. Probabilistic neural network (PNN) is applied to indoor location system aiming at environment of strong noise indoor and the reason of PNN applied to indoor location system based on powerline is discussed in detail. According to characteristics of transmitted signal by powerline, the signal is firstly pretreated and then transformed by Fast Fourier Transform (FFT) before it is transmitted to PNN algorithm in order to effectively extract position information included in data by PNN. The test shows that network training speed of PNN is fast, it has a strong ability to resist interference, with having good indoor positioning accuracy and PNN is much better than K-Nearest Neighbor (KNN) and Counter Propagation Network (CPN) indoor positioning algorithm in indoor position system based on powerline.

Key words: Probabilistic neural network (PNN) algorithm, power line, indoor positioning, received signal strength indicator (RSSI).

INTRODUCTION

In recent years, people are gradually increasing the needs of indoor positioning information service. At present, indoor positioning systems are A-GPS, Active Badge, Active Bat, RADAR and RFID and so on at home and abroad because the traditional GPS and cellular network positioning technology can not satisfy the requirement of indoor positioning. Although the positioning technology above has obtained the certain effect and some even location precision is very high, these systems need to add new hardware, system deployment of complex, high cost, poor scalability and usability to improve (Anwei and Zhiguang, 2010; Yubin et al., 2011; Dianjun and Yunfeng, 2010; Huang, 1999).

In view of the above problems, this paper designs a positioning system based on common indoor power line to position indoor mobile node. The power line positioning (PLP) is that firstly, let the signal of certain frequency into power lines indoor, transmit the signal to the air by power lines and have the signal cover whole space measured, and then the receiver accepts signals from the power line to complete the precise positioning of the moving target. On the one hand, compare with other indoor positioning technology, the positioning system is not needed to add too much auxiliary equipment to meet demand of signal emission source, moving target in the technology. On the other hand, Users can configure the number of signal transmitter, according to the size of interior space and it is flexible to implement scalability and easy deployment of positioning system. According to characteristics of power line positioning signal, the paper focus on indoor mobile node localization algorithm and precision analysis.

DATA ACQUISITION OF INDOOR POSITIONING BASED ON POWER LINE

In fact, If only signal of line of sight is dominant, orientation results based on these technologies, such as Time Of Arrival (TOA), Time Difference Of Arrival (TDOA) and Direction Of Arrival (DOA), is reliable. The above positioning technologies cannot be applied in indoor environment because multipath phenomenon of indoor environment is serious. In addition, it is difficult to do accurate synchronization which is needed in many

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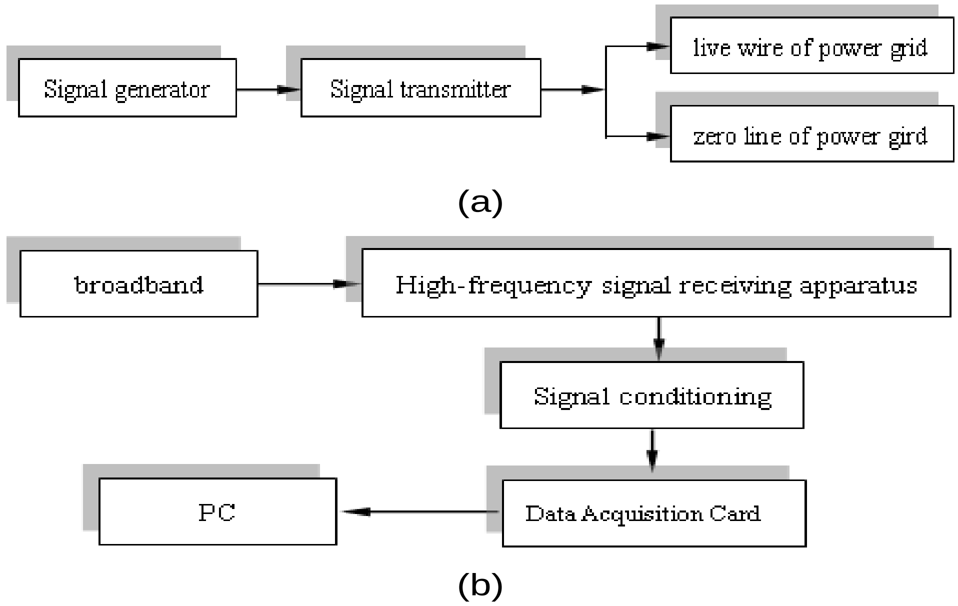

Figure 1. Sampling principle of indoor signal intensity based on power line (a) signal transmitting unit of test bench (b) signal receiving unit of test bench.

applications between transmitter and receiver by information of TOA or TDOA. Another alternative positioning method is RSSI that is based on the strength of sampled signal. The transmitted strength of signal is certain, but the different receiving node receive different strength because the strength of signal is lost in the process of communication, so these strength information of signal is transformed into a position information and it do not measure the time and angle of arrived signal. The way is the researched positioning model in the paper (Mei and Chen, 2010; Paul and Wan, 2009).

The signal acquisition principles of PLP are as follows. In a power line positioning system, the signal generator generates some signals which frequency is 100 kHz ~ 2 MHz and these signals are inputted to power line at last, as shown in Figure 1(a). Transmitting device of different frequencies is placed in different area of the interior room. The signal receiving unit is placed in the mobile node, its working principle is shown in Figure 1(b), and indoor electromagnetic signal is converted to a voltage signal by the unit with a broadband antenna and high-frequency signal receiving apparatus. The receiving device collects all kinds of signals with different frequency and lets these signals form a vector. The information of each signal strength is finally extracted through the FFT transform. Each element of the vector is the signal strength from transmitting device laid in particular position. Thereafter the vector is entered in the appropriate positioning algorithm. Each element of the input vector from one position is different. So the input vector corresponding to the certain location can be judged by positioning algorithm. And the output of positioning algorithm is also a vector which reflects the coordinate value of mobile node. Thus the positioning system accomplished the positioning for mobile node.

INDOOR POWER LINE POSITIONING ALGORITHM BASED ON PNN

From the previous result, the information, which is gotten by indoor power line positioning system, is intensity information of electromagnetic wave (RSSI) which is radiated from power line. According to received signal strength indicator (RSSI), the electronic map is built. The PNN algorithm is used to process RSSI of signal after careful comparison and demonstration. The essence of indoor power line positioning based on PNN is to identify which pattern class of location detected vector from unknown sources belongs to. PNN achieves the Bayesian decision by the probability density function of known data vector with nonparametric estimation. The working process of positioning system is as follows. Firstly, when the positioning system works, the unknown location information vector is inputted in the artificial neural network framework, and then it will be judged to which place the unknown data vector most likely come from.

Indoor positioning theory based on PNN

PNN is a kind of neural network which can be used for pattern classification and its essence is a parallel algorithm which derives from minimum Bayesian risk criterion. Class conditional probability of pattern $P(x|G_i)$ is used as a basis of PNN. It is only necessary to estimate distribution parameters to know the position information if the distribution of *priori* knowledge is known, but it is difficult to know true probability density because all the classical parametric density are single peak and many parametric density of practical problems are multiple peaks in most of pattern classification problems (Zhifeng and Jianguo, 2002), so, the probability density estimation of the parametric form should be solved. Suppose that number of indoor location beacon is n, which constitute all class and they are G_1, G_2… G_n, every kind of beacon prior probability is $P(G_i)$ (i = 1, 2…n, following the same). For the input vector, assume that the conditional probability of each category (each the indoor location) is $P(X|G_i)$. According to the Bayes theorem, posterior probability P (G_i | X) of the overall G_i is defined as:

$$P(G_i|X) = \frac{P(X|G_i)P(G_i)}{P(X)}$$

$$= \frac{P(X|G_i)P(G_i)}{\sum_{k=1}^{n} P(X|G_k)P(G_k)} \quad (1)$$

Discriminant criterion of PNN can be formulated as follows:

$$X \in G_i, \text{ if } P(G_i|X) > P(G_j|X), \quad i \neq j; \quad i, j = 1,2,3 \ldots, n. \quad (2)$$

If the prior probability is known, thus, Bayes criterion can be rewritten as:

$$X \in G_i \text{ , 若 } P(X|G_i)P)(G_i) > P(X|G_j)P)(G_j)$$

$$, i \neq j; i, j = 1, 2, \ldots, n. \quad (3)$$

If sampled number of each class data are same, that is:

$P(G_i) = \frac{1}{n}$, thus, the posterior probability of overall is can be recast as:

$$P(G_i|X) = \frac{P(X|G_i)P(G_i)}{P(X)}$$

$$= \frac{P(X|G_i)P(G_i)}{\sum_{k=1}^{n} P(X|G_k)P(G_k)} = \frac{P(X|G_i)}{\sum_{k=1}^{n} P(X|G_k)} \quad (4)$$

From the above, it can be seen that for the different i, the denominator of formula (4) is same, then, can get the following simpler discriminate criterion:

$$X \in G_i, \text{ if } P(X|G_i) > P(X|G_j), \quad i \neq j; i, j = 1, 2, \ldots, n.. \quad (5)$$

As usually, can only give the training samples, $P(X|G_i)$ is unknown. In this case, $P(X|G_i)$ should be estimated. Estimation method of Parzen window function density is the most general method of density estimation, and then the method is also applicable on the multi peak mixing condition. As long as the sample is enough, it can always be guaranteed to converge to any complex unknown density.

If we set that pattern G_i to have N_i pattern samples which are X_i^j (i= 1, 2,…n; j = 1, 2, … N_i), Parzen Window function is Gauss kernel function; then for Pattern G_i, Class conditional probability density estimation of Parzen Window function $P(X|G_i)$ can be written in the following formula:

$$P(X|G_i) = \frac{1}{N_i(2\pi)^{\frac{n}{2}}\sigma^n} \times \sum_{k=1}^{N_i} \exp\left[-\frac{(X - X_{G_i}^k)^T(X - X_{G_i}^k)}{2\sigma^2}\right] \quad (6)$$

Where, n = dimensionality of measurement space, $X_{G_i}^k$ = kth training pattern from category G_i, σ = smoothing parameter (the width of Parzen windows) and k= pattern number.

As mentioned above, the above theory can realize power line indoor positioning.

PNN indoor positioning model

According to the above theory, the network structure of PNN indoor positioning shown in Figure 2. It mainly consists of three layers: the first layer is input layer which output vector shows the degree of approximation between the input vector and training samples. The output vector of second (model layer) lets all classes which are associated with input vector together; it is the output network that represents the probability vector. The third layer (category layer) makes a choice that the biggest probability category is 1 and other categories are 0 through the competing transfer function of second layer. Assuming we aim to implement Parzen window estimation and there are a total of Q samples of M dimension which are randomly selected from the

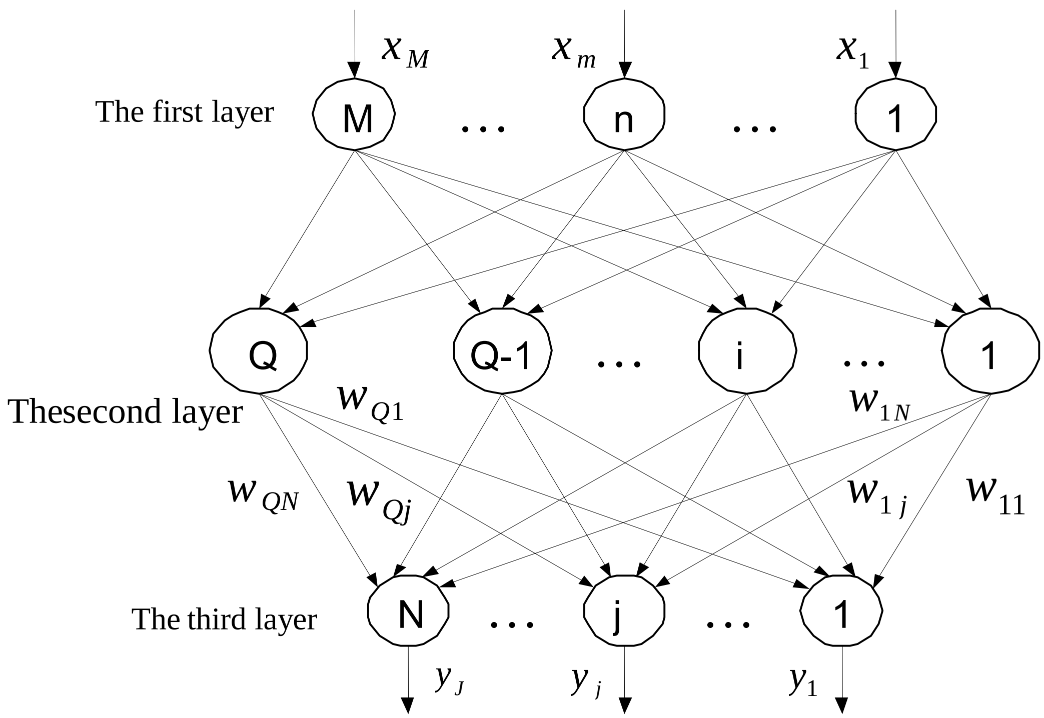

Figure 2. Structure of PNN of indoor position abased on Power line.

n-categories; in this case, the input layer consists of M input units and each input unit is connected to the Q model units. Number of pattern layer unit is Q and is equal to the number of training samples. Each model unit is connected with the unit of a category in N categories of the category layer which corresponds to this model unit (Xin and Ali, 2005; Quan and Huiying, 2011). The PNN learning algorithm is described as follows:

(1) The original data pretreatment: Firstly, signal strength information of the sampling data in the test field is extracted through the FFT transformation. Different kinds of frequency involved in the current signal will be got by spectrum analysis on the signal via FFT. Thus, the target frequency will be obtained. To have sampled data reflect the actual process, these sampling data noise should be removed after the FFT because sampling data in the field consist of many unexpected interference which mingle with some dummy data. It is found in the actual test that value of these data are often raised or reduced at the same time. By analysis, it is found that such interference is mainly due to the high-frequency signals of the power line, such as the number of switching power supply, motor starters, which the frequency of the signal may be the same as the frequency of signal which is sent by the positioning transmitter, thereby makes strength of these signals increase. It is necessary to eliminate such interference. It is presented that input network and output data is constrained in [0, 1] interval in order to eliminate the interference by applying data transformation of Equation (7).

$$x = (0.96 - 0.06)\frac{x - x_{\min}}{x_{\max} - x_{\min}} + 0.06 \qquad (7)$$

(2) Determine radial basis function center of the mode layer: Set up respectively the training set of sample input matrix P and the output matrix T as follows:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1Q} \\ p_{21} & p_{22} & \cdots & p_{2Q} \\ \vdots & \vdots & \vdots & \vdots \\ p_{M1} & p_{M2} & \cdots & p_{MQ} \end{bmatrix} \qquad (8)$$

$$T = \begin{bmatrix} t_{11} & t_{12} & \cdots & t_{1Q} \\ t_{21} & t_{22} & \cdots & t_{2Q} \\ \vdots & \vdots & & \vdots \\ t_{N1} & t_{N1} & \cdots & t_{NQ} \end{bmatrix} \qquad (9)$$

Where, p_{ij} represent the jth training sample's ith input variable; tij is the jth training sample's ith output variables, M is the number of variables of indoor beacons; N is the dimension of the output variable; Q is the number of

Figure 3. Test bed: Sensor laboratory (one floor: 8 m × 25 m).

samples of the training set.

The radial function center (radial basis function neural weights) which correspond to Q neurons of hidden layer is the transpose of the input vector as follows:

$$C = P' \quad (10)$$

(3) Determine the hidden layer neurons variance: The variances which Q hidden layer neurons correspond to are as follows:

$$\vec{\sigma} = [\sigma_{11} \cdots\cdots \sigma_{1Q}]' \quad (11)$$

Initial variance can be used:

$$\sigma_{1i} = \frac{d_{\min}}{\sqrt{2}} \quad (12)$$

$d_{\min}$ is the minimum distance between the selected centers of neuron to other centers of neuron.

(4) Determine the weights between the hidden layer and output layer: When the radial basis function of hidden layer neurons and the variance are determined, the output of hidden layer neurons can be calculated by formula (13)

$$\vec{a}^i = \exp(-\frac{1}{2\vec{\sigma}^2}\|C - \vec{p}_i\|^2) \quad (13)$$

Where, $\vec{p}_i = [p_{11}, p_{12}, \cdots, p_{1Q}]'$ is the ith training sample vector, and note $\vec{a}^i = [a_1^i, a_2^i, \cdots, a_Q^i]$. From the above equation, It is found that if only distance is 0, the output is 1, the more distance, the small output. Therefore, we can get that radial functions are only generated in response to those input which is close to input weight vector (distance to a central location is close to 0). So, the response of the hidden layer to the input signal is only maximum in the central location of the function; it is namely partial response. The network has good classification and identification capabilities.

Connection weights W between hidden layer of PNN and output layer is taken as the output layer matrix of the training set:

$$W = T \quad (14)$$

(5) Calculate neuron output of the output layer: When the connection weights between the hidden layer and output layer neurons is determined, as shown in Figure 3, we can calculate the output of output layer neurons as follows:

$$B^i = W \cdot a^i \text{, i=1, 2, … N} \quad (15)$$

$$\bar{y}^i = compete(B^i) \text{, i=1, 2, … N} \quad (16)$$

It can be seen from Equation (8) that a vector is gotten after each indoor location information of the sample passes the radial function. Thus, as this vector is passed to a competitive layer, value of elements which correspond to the sample with maximum is 1, and value of the remaining elements is 0. In other words, only the sample which has a smaller distance from location information template can win in the final competition layer and can be considered sample of winning is the true location of the current target. With increase in the number of samples Q, there will be more PNN hidden layer network, the accurate network positioning. At last, the PNN with a mass of train data vector needs to be trained before working properly. Thereafter PNN will need to be tested with test data vector and used for indoor positioning when the requirement of accuracy has been satisfied.

TEST AND ANALYSIS

For the purpose of confirming the performance of indoor powerline positioning by PNN algorithm, in this paper, we will use the room shown in Figures 3 and 4 to do the indoor positioning test and list the merits of the algorithm by comparing it with k-Nearest Neighbor (KNN) and Counter Propagation Networks (CPN) positioning algorithm.

The mobile node of this test is shown in Figure 5. The receiving antenna is fixed on an intelligent car. While

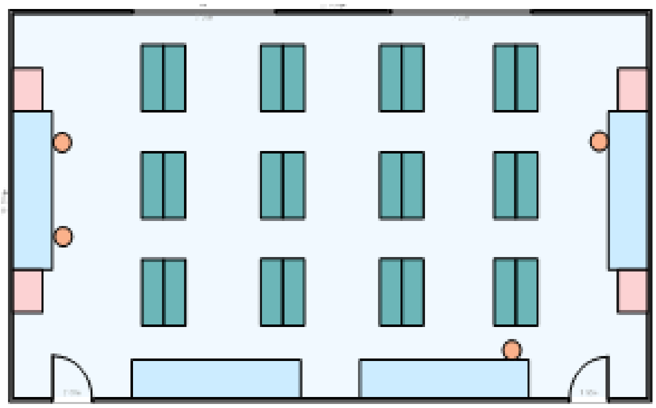

Figure 4. Plane structure diagram.

Figure 5. The mobile node of test.

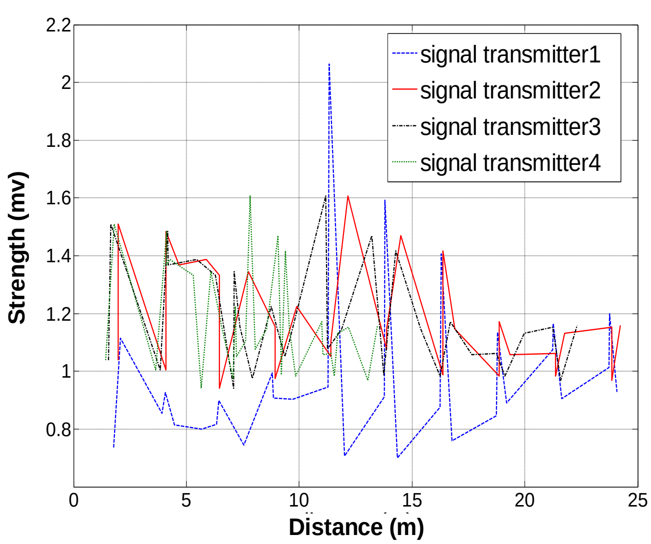

Figure 6. Relation curve between signal strength and distance.

carrying on the test, the antenna receives all kinds of electromagnetic signals transmitted by powerline and these signals are sent to host computer by the signal receiving device. Meanwhile, the track of intelligent car is controlled by wireless remote controller.

The test room is a sensor laboratory as shown in Figure 3; while the plan structure of test room is as shown in Figure 4.

Firstly, the relationship between the intensity and distance of signal propagation through the graph of Figure 6 is analyzed. In Figure 6, the abscissa is distance between signal transmitter and mobile node, while the ordinate is strength of signal which is received by the mobile node in an indoor place. The most widely applied signal propagation model is the log-normal shadowing mode, as shown in Equation (17) (Saxena et al., 2008):

$$P(d)_{dBm} = P(d_0)_{dBm} - 10n\log(\frac{d}{d_0}) + X_0 \qquad (17)$$

Where, $P(d_0)$ is the path loss at reference distance of d_0 meters. d_0 is assumed to be 1 m, and n is the path loss exponent. ($X_0 \sim (0, \sigma^2)$ is the RSSI measurement for noise modeled as zero mean while Gaussian with variance σ^2. The log-normal model cannot fully characterize the relationship between RSSI data and distance.

The graph of Figure 6 shows that function relation between signal intensity and distance does not satisfy the formula (12). Analysis reveals the main reason is caused by the following:

1) Multipath phenomenon has curve that did not satisfy the Equation 17.
2) The power line of some of the rooms is not around the room but is arranged under the floor; therefore appear phenomenal as shown in Figure 6.

Figure 7 shows the positioning performances of the three positioning algorithms mentioned above on the condition that the size of test area is 8 m × 25 m, the positioning node is 45 and with different number of beacon. The number of signal transmitter is increased from one to four, the average positioning error of PNN algorithm is greatly reduced and obviously the accuracies of the other two algorithms are not as high as PNN algorithms. When the quantity of signal transmitter is equal to four, we can get very high positioning accuracy of unknown beacon node. But as the quantity of signal transmitter exceed four, the positioning accuracy of unknown beacon node will not be improved significantly. So, it can be concluded from Figure 7 that when the number of signal transmitter exceeds a certain amount, the positioning accuracy cannot be improved significantly with the increase of the number of signal transmitter. From what has been discussed above, we may draw the conclusion that PNN

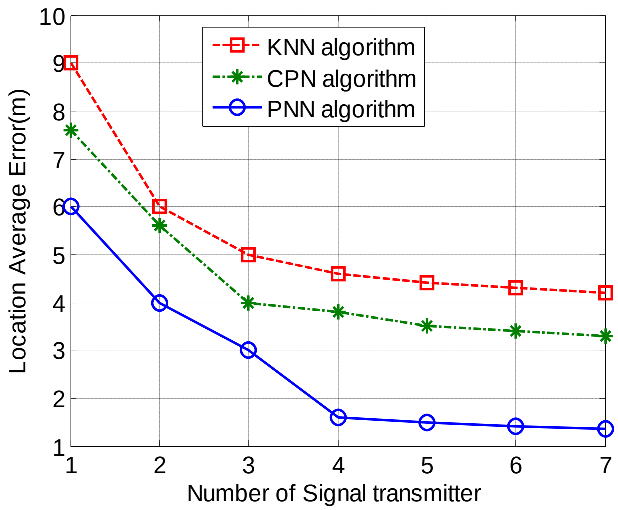

Figure 7. Positioning performance under different number of signal transmitter.

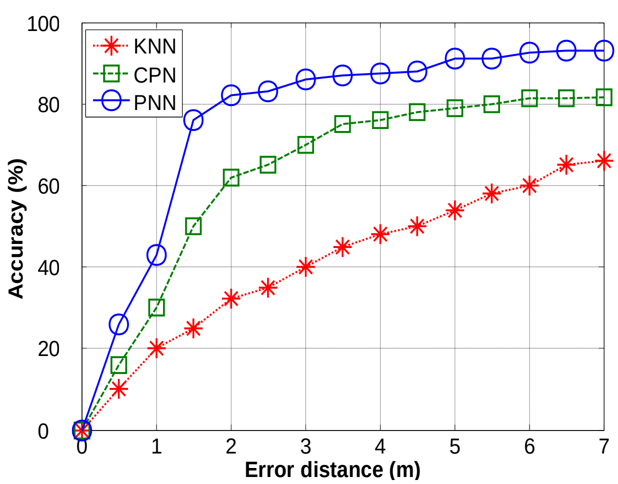

Figure 8. Accuracy comparison of different techniques.

algorithm can be used to achieve meter sized positioning, so, the positioning of indoor based on power line by PNN is suitable.

Figure 8 reports the positioning accuracy comparison of different techniques in different error distance and shows the cumulative distribution function (CDF) of the estimation errors of those 45 positions. The estimation error is defined as the absolute distance which is the difference between the estimated target's location and the actual target's location. Where, on the test condition that the number of signal transmitter is 4 and length of the area is increased from 0.5 to 7 m, PNN algorithm decreases average localization error with increasing the error distance. Figure 8 also shows that comparing to KNN and CPN algorithm, the positioning accuracy is obviously higher than other two algorithms. For PNN, 24% of the estimated positions are within an absolute error distance of 0.6 m, and 78% estimations within the error of 1.5 m. When horizontal coordinate value is 2 m, the accuracy of PNN approach is 82.1% while those of KNN and CPN are 31.19 and 62.23%, respectively. There are two reasons for phenomenon: on the one hand, the PNN can precisely characterize the temporal RSS fluctuation; on the other hand, PNN method can more efficiently reduce such multipath effects. From what has been discussed above, PNN positioning algorithm is more effective than other algorithms in indoor positioning based on power line. PNN algorithm can get minimum distance error between the beacon node and unknown nodes in the statistical sense by reasonably setting beacon node position as far as possible. From the above result, PNN algorithm is very suitable for the indoor positioning based on powerline.

Conclusions

By combining with the characteristics of indoor powerline RSSI and the mathematical analysis and research on signal of powerline, the idea of indoor positioning for moving target by PNN algorithm is introduced and related theory is used for the pretreatment of original data to enhance the positioning accuracy. The test results show that compared with other algorithm, the PNN algorithm which is used for indoor positioning with no hardware expansion can improve positioning accuracy significantly and achieves the measurement of low-energy-waste and high positioning accuracy. The method is easily realized in the engineering, the diagnosis robustness for sensor measurement noise is strong and the indoor positioning accuracy rate is higher. With gradual acquisition and knowledge of positioning, the PNN expands continuously and the accuracy of positioning will be higher. Obviously, this proves the advantages of the PNN algorithm. In order to improve the positioning accuracy and data reliability, the follow-up work should carry on the following two aspects: First, demonstration and design of hardware about reliability and practicability should be finished. Secondly, further research on indoor positioning data and improvement of the positioning system performance on the premise that the algorithm's robustness is ensured.

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