www.sensorsportal.com

Sensors & Transducers

A Novel Wireless Localization Fusion Algorithm: BP-LS-RSSI

Yuanqiang WANG, * Shang Fu HAO, Anyi LAN, Jie YANG
School of Information Science and Engineering, Hebei North University, He Bei, 075000, China
E-mail: hbnuwyq@126.com, 184172328@qq.com, papernetwork@163.com

Received: 6 October 2013 /Accepted: 22 November 2013 /Published: 30 December 2013

Abstract: With the increasing demand for location-aware services, high-precision indoor positioning play more important role for some applications. People also put forward higher requirements on positioning accuracy. BP neural network as a kind of typical forward neural network has the very strong self learning ability and can approximate any discontinuity of rational function. This paper proposes BP-LS-RSSI localization model, then use the model to fix received signal strength indication (RSSI) values for positioning by the LS algorithm. Since the positioning accuracy do not satisfy the needs by the traditional LS algorithm, we transfer the RSSI values into confidence weights according to the topology of network, then use the weighted least squares (LS) method to further optimize the positioning system. Simulation results show that the proposed algorithm has obvious increase to the positioning accuracy is a feasible localization algorithm. *Copyright © 2013 IFSA.*

Keywords: BP neural network, Least square algorithm, RSSI, Reliability weight.

1. Introduction

With the advancement of communications technology, embedded computing technology, micro-processing technology and sensor technology, the wireless sensor networks (WSNs) have began to receive widely attention as its perception, computing and communication capabilities [1, 2]. For most applications, only the combination of location information, the sensor data obtained have practical significance. The rapid development of wireless sensor networks make wireless positioning technology has become one of the main ways in the military , production, all areas of life, which is widely used. Artificial Neural Network (ANN) is a man-made neural network structure can implement some functions, based on the understanding of the human brain. ANN has been widely used in various fields, in the process of wireless localization, multi-sensor fusion positioning, which is got the people's attention. By training the neural network system, it is possible to find out the new and effective way to solve non-line-of-sight (NLOS) problems for wireless positioning [3, 4].

According to whether measured the distance in the process of localization, wireless localization algorithms can be divided into range-free and range-based algorithm. The algorithm based on range-free, which do not measure the distance and angle, but calculate the location by network connectivity information. This type of algorithms do not require additional hardware support, the communication overhead is smaller. The range-based algorithms measure the between base station and mobile node by electromagnetic wave. There are some instances as following: angle of arrival (AOA), time of arrival (TOA), time different of arrival (TDOA), received signal strength indication (RSSI) [5-8]. As wireless communication environment becomes increasingly complex, a single localization algorithm can not meet the need of precise positioning, collaborative multi-station, multi- algorithm fusion is the main trends for positioning. We try to use BP neural network to amend the RSSI value, and then use the value amended to calculate location of mobile node by LS algorithm. Since the positioning accuracy does not satisfy the need by the LS algorithm, we transfer the RSSI values into confidence weights according to the topology of network, then use the weighted least squares method to further optimize the positioning system. Simulation results show that the algorithm significantly improved positioning accuracy is a viable localization algorithm.

The remainder of this paper is organized as follows: We discuss the RSSI model in Section 2. In Section 3, we overview the background of positioning algorithms. Section 4 emphasizes the fusion algorithm for positioning, Section 5 outlines simulation result, and Section 6 concludes this paper.

2. RSSI Model

The relationship between the launching power and receiving power of the wireless signal can be presented by formula (1),

$$P_{Bs} = P_{Ms} / r^n, \quad (1)$$

where P_{Bs}, P_{Ms}, r, n indicates the receiving power, launching power, distance and transmitted divisor respectively. Among them, the magnitude of the transmitted divisor depends on the environment of the signal transmission. Once we obtain the logarithm of formula (1), then we can get

$$10n\lg r = 10\lg P_{Ms}/P_{Bs} \Rightarrow 10\lg P_{Bs} = A - 10n\lg r, \quad (2)$$

Among them, A is the receiving power of the signal when the signal is transmitted in free space for 1m. $10n\lg r$ is the manifestation of the receiving power of signal converted into dBm, and it can be recorded as

$$P_{Bs}(dBm) = A - 10n\lg r, \quad (3)$$

In real environment, especially indoor environment, wireless signal will occur obstacle, which result in diffraction and multipath effects during the period of transmission. There is certain error between the actual and measured RSSI values. If there are more obstacles in room, the problem is more obvious. Therefore, the measured RSSI values, it is necessary to appropriately modified to make it more likely close to the actual values.

3. Overviews

3.1. BP Neural Network

BP neural network model is composed of input layer, hidden layer and output layer, which as shown in Fig. 1. Input layer has 6 signal strengths (RSSI) values supported by 6 base station nodes.

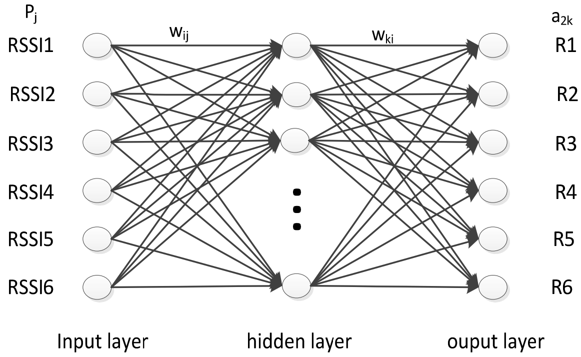


Fig. 1. BP neural network amendment model for RSSI measurements.

Input vector:

$$P = [RSSI\ 1, RSSI\ 2, RSSI\ 3, RSSI\ 4, RSSI\ 5, RSSI\ 6] \quad (4)$$

The number of neurons at hidden layer can be figured out with empirical equation, i.e. $N_2 \geq \log_2 T$, wherein N_2 is the number of neurons at hidden layer, while T represents the dimension of training sample. Increase of the number of neurons at hidden layer helps to improve localization accuracy yet bring about heavier calculation load. In view of the fact that this Paper uses a relatively small number of samples and attaches more importance to accuracy, 18 neurons are selected at hidden layer. The transfer function at hidden layer is sigmoid function $f_1(x) = \tanh(x)$, of which the input value can be arbitrary value, while the output value can be between -1 and +1.

The output layer is composed of 6 neurons and employs linear transfer function Purelin, i.e. $f_2(x) = kx$ whose output is the interpolation of fingerprint database. The output vector is given below.

$$O = [r_{21}, r_{31}, r_{41}, r_{51}, r_{61}, r_{71}], \quad (5)$$

Learning algorithm for BP network is as follows: assuming that the input layer is *P*, the number of input neurons is *r*, there are *s1* neurons at hidden layer, the corresponding activation function is f_1, there are *s2* neurons at output layer, the corresponding activation function is f_2, the output is A, and the target vector is *T*. w_{ij} represents the connection weight between input layer and hidden layer, while w_{kj} represents the connection weight between hidden layer and output layer.

The output of the i^{th} neuron at hidden layer:

$$a1_i = f_1(\sum_{j=1}^{r} w_{ij} p_j + b1_i), i = 1,2,...,s1 \quad (6)$$

Output of the K^{th} neuron at output layer:

$$a2_k = f_2(\sum_{i=1}^{s1} w_{ki} a1_i + b2_k), k = 1,2,...,s2 \quad (7)$$

Definition error function:

$$E(W,B) = \frac{1}{2}\sum_{k=1}^{s2} (t_k - a2_k)^2 \quad (8)$$

Determine the weight variation and the back propagation of error using gradient-descent algorithm; the change in the weight of output layer is proportional to the negative gradient of error function against the weight of output layer:

$$a2_k = f_2(\sum_{i=1}^{s1} w_{ki} a1_i + b2_k), k = 1,2,...,s2 \quad (9)$$

The weight of output layer is updated according to formula (10):

$$w_{ki}(t+1) = w_{ki}(t) + \Delta w_{ki}(t) \quad (10)$$

Change in the weight of hidden layer is proportional to the negative gradient of error function against the weight of hidden layer:

$$\begin{aligned} \Delta w_{ki}(t) &= -\eta \frac{\partial E}{\partial w_{jk}} \\ &= -\eta \frac{\partial E}{\partial a2_k} \cdot \frac{\partial a2_k}{\partial w_{ki}} \\ &= \eta (t_k - a2_k) . f_2' a1_i \end{aligned} \quad (11)$$

The weight of hidden layer is updated according to Formula (12):

$$w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij}(t) \quad (12)$$

3.2. LS Algorithm

Least squares estimation is an ancient and effective estimation method, because it does not require any prior knowledge, you only need to be estimated on the amount of the observed signal model, we can achieve signal parameter estimation, and easy to implement, and squared error can be minimized, so it is a very broad application of estimation methods. In general, the LS estimation can be described as:

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \quad (13)$$

where i=1,2,..., K. K means the number of BS nodes. Square both sides of Formula (2), we are able to get

$$\begin{aligned} d_i^2 &= R - 2xx_i - 2yy_i + (x_i^2 + y_i^2) \\ \Rightarrow xx_i - yy_i - 0.5R^2 &= \frac{1}{2}(x_i^2 + y_i^2 - d_i^2) \end{aligned} \quad (14)$$

where $R = \sqrt{x^2 + y^2}$, then formula (14) can be presented in the following matrix form,

$$H\theta = X \quad (15)$$

where

$$H = \begin{bmatrix} x_1 & y_2 & -0.5 \\ \vdots & \vdots & \vdots \\ x_k & y_k & -0.5 \end{bmatrix}, \theta = \begin{bmatrix} x \\ y \\ R^2 \end{bmatrix},$$

$$X = \frac{1}{2}\begin{bmatrix} x_1^2 + y_1^2 - d_1^2 \\ \vdots \\ x_k^2 + y_k^2 - d_k^2 \end{bmatrix}$$

Construction estimator θ performance indicators $J(\theta) = (X - H\theta)^T (X - H\theta)$, we can make the error reach to the minimum only when we can get $J(\theta)$ to become the minimum. Thus

$$\begin{aligned} \frac{\partial J(\theta)}{\partial \theta} &= \frac{\partial [(X - H\theta)^T (X - H\theta)]}{\partial \theta} \\ &= -2H^T (X - H\theta) = 0 \\ &\Rightarrow \theta = (H^T H)^{-1} H^T X \end{aligned} \quad (16)$$

The θ we get from this calculation is the estimate coordinate point of LS of MS. However, as the localization accuracy is not high enough and its function cannot be evaluated in the LS localization algorithm, therefore, its accuracy needs to be improved further.

4. Localization Algorithm

4.1. RSSI Value Amend by BP Neural Network

Fig. 2 shows five base stations (BS) and a mobile node (MS), the RSSI value can be obtained five groups ($RSSI1$, $RSSI2$, $RSSI3$, $RSSI4$, $RSSI5$). The real environment, especially in indoor environment, the wireless signal transmission encounter obstacles, which will occur diffraction and result in multipath effect. Some external factors impact the measured RSSI value; there is error between measured and actual RSSI values. We obtained BP neural network RSSI value is corrected so that the measured RSSI value is more likely closer to the actual value.

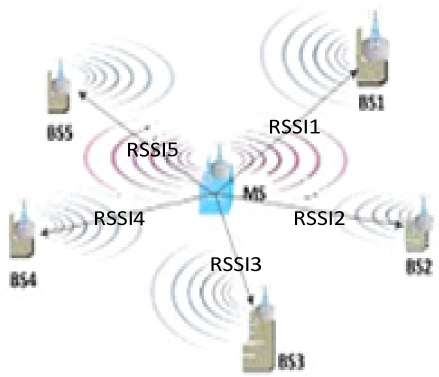


Fig. 2. Positioning node topology.

$(RSSI1, RSSI2, RSSI3, RSSI4, RSSI5)$
Transfer to reliability weight

$$(R1, R2, R3, R4, R5), \tag{17}$$

4.2. The Weighted LS Algorithm Based on RSSI Reliability Weight

We can obtain five groups distance value (d_1 , d_2 , d_3 , d_4 , d_5) by the RSSI value ($RSSI1$, $RSSI2$, $RSSI3$, $RSSI4$, $RSSI5$), transfer $(d_1, d_2, d_3, d_4, d_5)$ to a matrix, as shown in formula (18).

$$\begin{bmatrix} d_1 \\ d_2 \\ d_3 \\ d_4 \\ d_5 \end{bmatrix} \longrightarrow \left\{ \begin{bmatrix} d_1 & d_2 & d_3 & d_4 \\ d_1 & d_2 & d_3 & d_5 \\ d_1 & d_2 & d_4 & d_5 \\ d_2 & d_3 & d_4 & d_5 \\ d_1 & d_3 & d_4 & d_5 \end{bmatrix} \right., \tag{18}$$

we use LS estimation algorithm to calculate the location M times, then calculate the mean value(x_1 , y_1), (x_2 , y_2), (x_3 , y_3), (x_4 , y_4), (x_5 , y_5). The formula is shown in (19)

$$\begin{bmatrix} d_1 & d_2 & d_3 & d_4 \\ d_1 & d_2 & d_3 & d_5 \\ d_1 & d_2 & d_4 & d_5 \\ d_2 & d_3 & d_4 & d_5 \\ d_1 & d_3 & d_4 & d_5 \end{bmatrix} \xrightarrow{(H^T H)^{-1} H^T X} \begin{bmatrix} (x_1, y_1) \\ (x_2, y_2) \\ (x_3, y_3) \\ (x_4, y_4) \\ (x_5, y_5) \end{bmatrix}, \tag{19}$$

Location estimation of least-square method, although able to minimize the distance sum of squared residuals, but there are still some residual error can also cause, the error is difficult to avoid, weighting approach can be used to reduce this kind of error. We will basis points (BS) in the received signal strength (RSSI) into the weights of credibility to the weighted least square method (r). The optimal estimate final output node *(X, Y).*

$$(X, Y) = \left(\frac{x_1 r_1 + x_2 r_2 + x_3 r_3 + x_4 r_4}{4}, \frac{y_1 r_1 + y_2 r_2 + y_3 r_3 + y_4 r_4}{4}\right), \tag{20}$$

The LS - RSSI based on BP neural network data fusion localization algorithm can be represented as shown in Fig. 3.

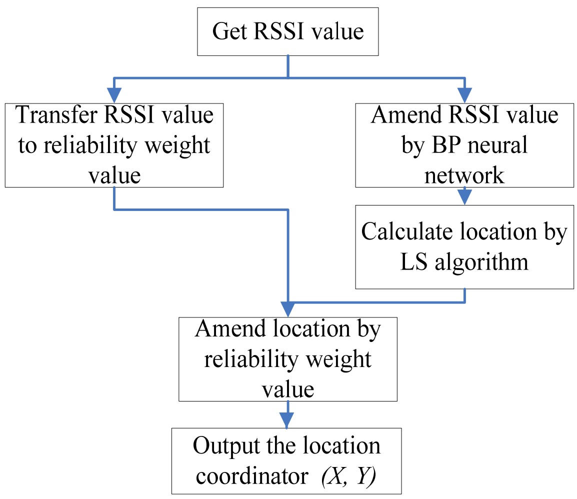


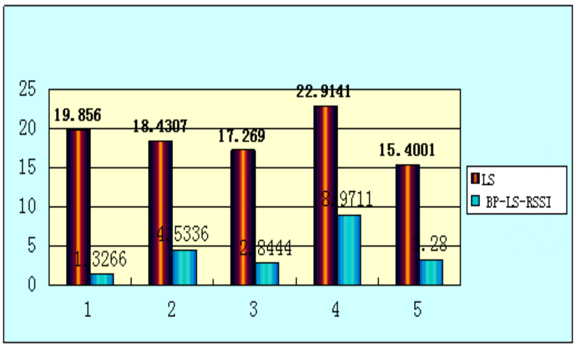
Fig. 3. LS - RSSI localization flow optimized by BP neural network.

5. Simulation

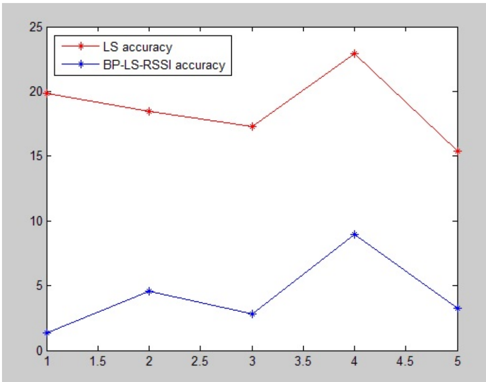
This paper uses the MATLAB simulation tools to validate the effectiveness of the algorithm, and make a comparison with the non-optimization algorithm. In simulation experience, MS emission power is 52 dBm, spread environment is represented by logarithm-normal distribution mode. Mainly for the positioning of the mobile node, selected $MS(1000,2000)$ as be estimated node, $BS1(0,0)$, $BS2(3000\sqrt{3},3000)$, $BS3(0,6000)$, $BS4(-3000\sqrt{3},3000)$, $BS5(3000\sqrt{3},3000)$ as the five base station node. In the 2D coordinates, the use of square error AVG of positioning results as a general positioning accuracy, as shown in formula (21).

$$AVG = \sqrt{(X-x)^2 + (Y-y)^2}, \tag{21}$$

Fig. 3 shows comparison of the precision for LS and BP-LS-RSSI.



(a)



(b)

Fig. 4. The comparison of accuracy between LS and BP-LS-RSSI.

We can be seen from the Fig. 4 BP-LS-RSSI localization algorithm of the weighted fusion accuracy compared with the single LS algorithm has significantly improved; experimental simulation show that LS-RSSI based on BP neural network data fusion location algorithm is a feasible and effective method.

6. Conclusions

Based on the study of LS, RSSI localization algorithm and BP neural network algorithm, proposed a BP-LS-RSSI fusion algorithm. The method using the learning feature of neural network is faster and the ability to approximate any nonlinear mapping, make it suitable for complicated multipath environment. By BP neural network correction for RSSI value, effectively restrain the signal in the process of NLOS transmission error, and through the optimization of base station selection, rotate the base station positioning, and the reliability weighted effectively eliminates the error of LS localization algorithm, significantly improve the positioning accuracy. Simulation results show that, this positioning algorithm does not require hardware extension, a small amount of calculation; the ordinary LS algorithm is effective to steadily improve the positioning accuracy.

Acknowledgements

The authors would like to thank the research of Fixed Assets Management & Evaluation system Based on the technology of Internet of things, which supported by the Science and Technology Bureau of Zhang Jiakou, Hebei province. for their support in this research.

References

[1]. J. Liu, Q. Wang, J. Wan, J. Xiong, B. Zeng, Towards Key Issues of Disaster Aid based on Wireless Body Area Networks, *TIIS*, Vol. 7, 2013, pp. 1014-1035.

[2]. H. Suo, J. Wan, L. Huang, C. Zou, Issues and Challenges of Wireless Sensor Networks Localization in Emerging Applications, in *Proceedings of the International Conference on Computer Science and Electronics Engineering*, Hongzhou, 2012, pp. 447-451.

[3]. J. Liu, Q. Wang, J. Wan, J. Xiong, Towards Real-Time Indoor Localization in Wireless Sensor Networks, in *Proceedings of the 12th International Conference on Computer and Information Technology (CIT)*, 2012, pp. 877-884.

[4]. M. Chen, J. Wan, F. Li, Machine-to-Machine Communications: architectures, standards, and applications, *KSII Transactions on Internet and Information Systems*, Vol. 6, 2012, pp. 480-497.

[5]. Y. Weng, W. Xiao, L. Xie, Total Least Squares Method for Robust Source Localization in Sensor Networks Using TDOA Measurements, *International Journal of Distributed Sensor Networks*, Vol. 2011, 2011.

[6]. A. De Angelis, J. Nilsson, I. Skog, P. Händel, P. Carbone, Indoor Positioning by Ultrawide Band Radio Aided Inertial Navigation, *Metrology and Measurement Systems*, Vol. XII, 2010, pp. 447-460.

[7]. F. Zhu, Z. Wei, B. Hu, J. Chen, Z. Guo, Analysis of indoor positioning approaches based on active RFID, in *Proceedings of the 5th International Conference on Wireless Communications, Networking and Mobile Computing,* Beijing, China, 2009, pp. 5182-5185.

[8]. J. Liu, Q. Wang, X. Chen, W. Huang, A Novel Wireless 3D Localization Method Supported by WSN, I*nternational Journal of Online Engineering (iJOE)*, Vol. 9, 2013, pp. 9-12.