Send Orders for Reprints to reprints@benthamscience.ae

The Open Fuels & Energy Science Journal, 2015, *8*, 281-286

Open Access

Underground Coal Mine Positioning System Based on RSSI Positioning Algorithm Improved Through the BP Learning Training

Yan-Xiu Chen*

School of Electrical Engineering, Guizhou Institute of Technology, Guiyang, China

Abstract: The influence of the coal mine geographic environment on the electromagnetic transmission might result in the difficulty of wireless positioning under the mine. Concerning that the influence of the underground working face on the wireless signal attenuation is mainly reflected through the electricity path attenuated and based on the underground geographic differences, two corresponding electromagnetic loss models are established. Under the conditions of low energy consumption and no need for hardware devices, RISS algorithm is found suitable to be used in the underground coal mine. However, the problems of large error and poor precision still exist. This paper first introduces the standard deviation threshold, TSA, as decided by the practical environment; then compares it with the standard deviation, RSA, obtained by the calculation of every target node to finally obtain the modified value of RSS. Based on that, the BP algorithm is introduced for learning training, improvement of the positioning error rate and the system's positioning precision.

Keywords: Electromagnetic loss, error rate, learning training, RSSI algorithm, wireless positioning.

1. INTRODUCTION

The coal mine geographic environment is unique. It is often faced with many unfavorable factors, including uneven working face, large fluctuations, long and narrow roadways, lots of corners and branches, all-pervasive dust, high gas content and air humidity and a large number of comprehensive coal mining devices. All these might cause a great influence on the electromagnetic wave transmission. As a high-risk industry, the coal mine has a high requirement of the precision of the coal mine's positioning system. The real-time tracking of relevant personnel's position information is necessary. When accidents happen, the geographical position of relevant personnel should be identified immediately for the rapid rescue. Based on the above characteristics of the coal mine geographic environment, the coal mine positioning system should adhere to the following principles [1-3]:

1) Try to decrease the complexity of algorithm and reduce and energy consumption of the beacon node so as to extend the service life of nodes;

2) The algorithm is based on the self-organizing network. The distributional data treatment assigns the tasks to different nodes so as to reduce the expenditure of nodes and avoid the limited beacon node treatment capacity from influencing the robustness of the network;

3) The underground situation of the coal mine is extremely complex. Its geological structure and external environment will cause a great influence on the electromagnetic wave transmission.

Under these circumstances, the precise positioning is difficult. The positioning system should have sound fault-tolerant capability and adaptive capability so as to ensure the robustness of the network.

In order to meet the above requirements, the algorithm design of the underground coal mine positioning system should be based on the underground electromagnetic wave transmission.

2. ELECTROMAGNETIC WAVE TRANSMISSION MODEL

Under the complex environment of the coal mine working face, the influence of the wireless transmission on the attenuation of the wireless signals is mainly reflected as the path attenuation index. The path attenuation index could fully demonstrate the attenuation of wireless signals and the loss of spatial diffusion caused by the topographic fluctuations. Besides, the path attenuation index will change along with barriers and topographical fluctuations. The comprehensive coal mining machines will also absorb some signals. All in all, many factors can result in the quick attenuation of wireless signals under the coal mine. Concerning the electromagnetic transmission characteristics under the coal mine and based on the environment adaptability of specific signals, this paper finds out the wireless wave underground roadway transmission loss model close to the practical environment.

The underground wireless system should choose the working frequency within the UHF (Ultra High Frequency, 30~3,000MHz). The electro-magnetic transmission loss during the frequency section is relatively small and the transmission distance is relatively far.

*Address correspondence to this author at the School of Electrical Engineering, Guizhou Institute of Technology, Guiyang, China;
Tel: 18986139113; E-mail: Hunter2011@foxmail.com

1876-973X/15

Electromagnetic signals feature multimode transmission in the coal mine roadway. In the periphery of the transmitting antenna, there are lots of higher-order modes. When electromagnetic signals undergo certain transmission distance, the transmission loss based on the higher-order mode is higher than that based on the lower-order mode. Since lots of higher-order modes are attenuated and depleted, the electromagnetic signals thus enter the transmission mode based on the lower-order modes featuring the fundamental modes. At the moment, the attenuation of the electromagnetic signals will slow down. Therefore, the transmission of electromagnetic signals in the coal mine roadway can be divided into two transmission areas, namely the near-field area and the far-field area. The coal mine roadway can be a straight line, a corner, a branch and so on. They are responsible for transmitting different attenuation characteristics.

Fig. (**1**) shows the electromagnetic loss of electromagnetic signals in different distances and different roadway breadth.

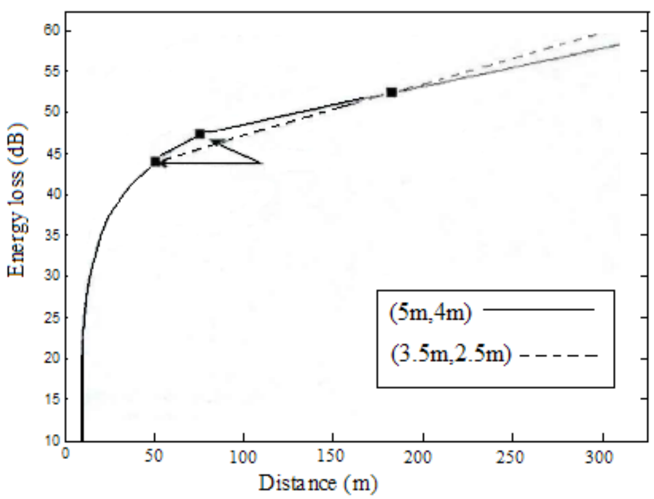

Fig. (1). Transmission diagram of electromagnetic signals in the coal mine roadway.

From Fig. (**1**), it can be seen that the energy loss occurs in the short distance during the transmission of the electromagnetic waves in the coal mine roadway. Thus, it is the near-field area. The energy loss is high in the long distance. Thus, it is the far-field area. The medium-near-field area in the roadway with the section of (5m, 4m) is longer than that in the roadway with the section of (3.5m, 2.5m). Fig. (**1**) also shows that the battery loss difference between the near-field area and the far-field area is large, which should be an important factor to considerate during the confirmation of the wireless positioning algorithm [4].

Transmission loss of electromagnetic signals in the near-field area. In the near-field area, electromagnetic signals feature the multimode transmission. Their transmission style is quite similar to that in the free space. Thus, the transmission model of the roadway in the near-field area is shown below:

$$PL(d) = PL(d_0) + 10klog(\frac{d}{d_0}) + X_\sigma \quad (1)$$

Where, PL(d) stands for the path loss (dB) after the radio wave transmission distance of d; Xσ stands for the random variable of the normal distribution of (0, 1);σ stands for the standard deviation and the empirical value is set to be 4-10:k ＝2～5 stands for the path attenuation factor; $PL(d_0)$ stands for the path loss of the free space transmission when d=1m. Then:

$$\begin{aligned} PL(d_0) &= Loss(d = 0.001\text{km}) \\ &= 32.4 + 10k\lg(d = 0.001\text{km}) + 10k\lg(f) \\ &= 32.4 - 30k + 10k\lg(f) \end{aligned} \quad (2)$$

where: d stands for the spacing distance away from the information source(km); f stands for the radio wave frequency (MHz) [1].

In the far-field are of the roadway, the electromagnetic signals are transmitted in the lower-order mode style (mainly fundamental modes). It is similar to the transmission of electromagnetic signals among the waveguides. Thus, the transmission loss calculation formula based on the waveguide model in the far-field area is shown below:

$$\mathrm{PL}(\mathrm{d}) = \mathrm{PL}_2 + \mathrm{PL}_{\text{roughness}} + \mathrm{P}_{\text{tilt}} \quad (3)$$

The far-field area mainly considers the bending caused by the corners and branches of the roadway. During the calculation of the transmission loss, the bending-generated loss should also be taken into consideration. Then, the transmission loss in the far-field area is:

$$\mathrm{PL}(\mathrm{d}) = \mathrm{PL}_\mathrm{E} + \mathrm{PL}_{\text{roughness}} + \mathrm{P}_{\text{tilt}} + \mathrm{PL}_\mathrm{C} \quad (4)$$

where, PL_E stands for the transmission loss of electromagnetic signals based on the fundamental modes in the straight roadway; $\mathrm{PL}_{\text{roughness}}$ stands for the loss caused by the roughness of the roadway wall; P_{tilt} stands for the loss caused by the materials on the roadway wall; PL_C stands for the transmission loss of the electromagnetic signals based on the fundamental modes in the bended roadway [3-6].

The mobile node is located in the near-field area and the far-field area. The following formula can be employed to calculate the signal strength of various unknown nodes during the reception of the beacon nodes, respectively:

$$RSS = P + G - PL(d) \quad (5)$$

where, P stands for the transmitted power; G stands for the antenna gain.

RSSI positioning algorithm based on the learning training.

Based on the signal strength received by the nodes, RSSI algorithm calculates the transmission loss of signals. The wireless signal transmission theories or the empirical models transform the transmission loss into the distance. Then, the position of the nodes is estimated (see Fig. **2**).

At least three given nodes simultaneously receive the radio-frequency signal emitted by the same goal node to obtain its RSSI value and the coordinate of the target node.

The algorithm is characterized by low cost and low energy consumption. However, RSSI is highly vulnerable to the environment influence. Different environments, areas, directions, air flows, machinery devices, temperature changes and many other factors can result in different RSSI value. According to the traditional algorithm, when the RSSI value is changed into the corresponding distance value, the fixed empirical value is chosen, which could not reflect the influence degree of different areas on the wireless signals. The large error also results in poor positioning precision. This paper makes relevant improvement to make it suitable to the positioning in underground coal mine special environments.

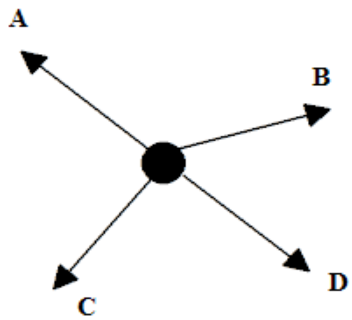

Fig. (2). RSSI schematic diagram.

3. BASIC ALGORITHM MODEL

The algorithm model is shown in Fig. (**3**).

The algorithm has the following characteristics [5-8]:

1. Every beacon node is required to have the same detection radius, R. If the goal node is within the detection radius, the positioning is conducted; otherwise, not.
2. Four groups of inputs are provided during every calculation, including the RSS value and its standard deviation (RSSSD) of the beacon node. The outputs are the plane coordinates corresponding to the goal nodes [9].
3. Based on the received RSS value, the goal node eliminates the abnormal RSS value. Count the number of the valid RSS value (0≤l(≤n). The standard deviation of all RSS values received is recorded as RSA.
4. The standard deviation threshold (TSA) is decided by the practical environment.
5. Based on each group of RSS value obtained each time, the RSS standard deviation (RSA) of the goal node should be calculated. Based on Eq. (5), the value

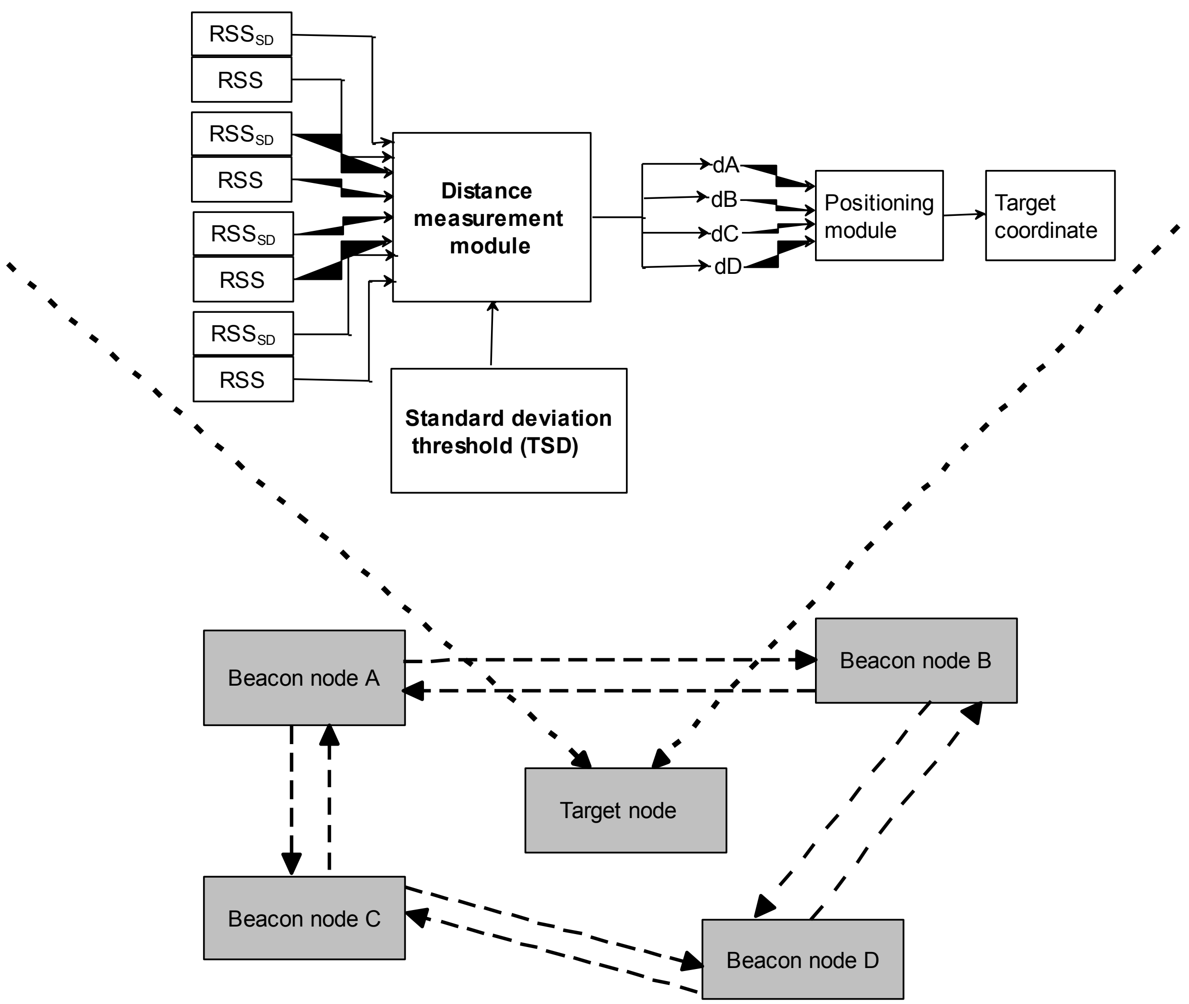

Fig. (3). Algorithm model.

of α can be obtained. Based on Eq. (4), the modified value of RSS is obtained.

$$\alpha = \begin{cases} 0.5\left(\dfrac{T_{\mathrm{SA}} - R_{\mathrm{SA}}}{T_{\mathrm{SD}}} + 1\right), R_{\mathrm{SA}} \le T_{\mathrm{SA}} \\ 0.5\left(1 - \dfrac{R_{\mathrm{SA}} - T_{\mathrm{SA}}}{T_{\mathrm{SD}}}\right), R_{\mathrm{SA}} > T_{\mathrm{SA}} \end{cases} \tag{6}$$

$$R_{\mathrm{avg}} = \alpha R_{\mathrm{avg1}} + (1-\alpha) R_{\mathrm{avg2}} \tag{7}$$

where,

$$R_{\mathrm{avg1}} = \frac{1}{m}\sum_{i=1}^{m} R_i, R_i \le \frac{1}{q}\sum_{j=1}^{q} R_j \tag{8}$$

$$R_{\mathrm{avg2}} = \frac{1}{q-m}\sum_{i=1}^{q-m} R_i, R_i > \frac{1}{q}\sum_{j=1}^{q} R_j \tag{9}$$

where, m means that there are "m" average values which are no larger than "q" valid values among "q" valid values:

Just as what is stated above, the traditional RSS algorithm faces the problem of large error and inadequate positioning precision. Here, the Error Back Propagation algorithm (abbreviated as BP algorithm) is introduced. The solution of the minimum value of the error function can help improve the precision and accuracy of the positioning system.

1. The input layer is composed of the four unknown nodes participating in the positioning and with the maximum RSSI value; while the output layer is made up of two plane coordinates with the corresponding labels.
2. Define the implicit strata to be two layers. According to the optimal node ratio of the first implicit layer to the second implicit layer obtained by Kuarycki through the experiment, the number of nodes of the first implicit layer is defined to be 15 and that of the second layer is 5.
3. The error function is defined to be the quadratic sum of the output expected value and the actual output difference value:

$$\exp = \frac{1}{2}\sum_{\mathrm{i}} (\mathrm{x}_{\mathrm{i}}^{\mathrm{m}} - \mathrm{y}_{\mathrm{i}})^2 \tag{10}$$

   where, yi stands for the output expected value; xi stands for the actual output difference value; and m stands for the output layer of the "m" layer.
4. The calculation of the error function can help judge whether the error has reached the preset value or the requirement that the learning times are higher than the preset maximum value. Otherwise, the next learning sample and its corresponding expected output will be chosen for the next round of learning [10].
5. Use the trained BP nerve network to amend the RSS modified value of the system positioning so as to reduce the positioning error and increase the positioning precision [7, 8].
6. The algorithm flow chart.

The algorithm flow chart of the model is shown in Fig. (**4**).

Step 1: Set the parameters of the BP network, including the number of implicit layers, the number of nodes and the precision BP;

Step 2: Initialize the weight value and the threshold;

Step 3: Calculate the input of every layer;

Step 4: Calculate the error of every layer according to the formula;

Step 5: Modify the weight value and the threshold value according to the negative gradient direction of the error function;

Step 6: Calculate the error and E of all sampling values during the same period;

Step 7: Compare E with the expected value and make a judgment. If the requirement is met, the process can be ended or return to Step 2 to repeat implementing a new cycle.

In order to verify the performance of the algorithm, a simulation experiment is conducted to compare the two algorithms under the same conditions. The simulation conditions are listed as follows: To simulate in a 200m×15m space within the long and narrow area of the coal mine roadway. The environment noise meets the normal distribution N(0,1); the detection radius (R) is 5m. Compare the relation between the beacon node proportion and the positioning error, and the relation between the roadway breadth and the positioning error during the simulation experiment of the two algorithms.

4. SIMULATION ANALYSIS OF THE ROADWAY BREADTH AND THE POSITIONING ERROR

10 beacon nodes with the given positions are preset, and 20 unknown nodes are randomly laid out. According to Fig. (**5**), it can be seen that with the increase of the referential nodes the positioning error before and after the algorithm improvement gradually decreases. Under the condition of the same referential nodes, the positioning error rate of the improved algorithm positioning is smaller than the positioning error rate before the improvement. Thus, it is suggested that the improved algorithm significantly improves the positioning precision.

5. SIMULATION ANALYSIS OF THE BEACON NODE DENSITY AND THE POSITIONING ERROR

Under the same conditions, a simulation test of the relation between the positioning system error and the roadway is conducted in terms of the two algorithms. The simulation test conditions are as follows: spacing distance between the beacon nodes is 50m, and the positioning precision of the unknown nodes changes along with the time under the different roadway breadths. From Fig. (**6**), it can be seen that the positioning error of the RSSI algorithm is greatly influenced by the roadway breadth, while the influence is significantly decreased after the improvement of the algorithm. This suggests that the improved algorithm is superior to the not improved one.

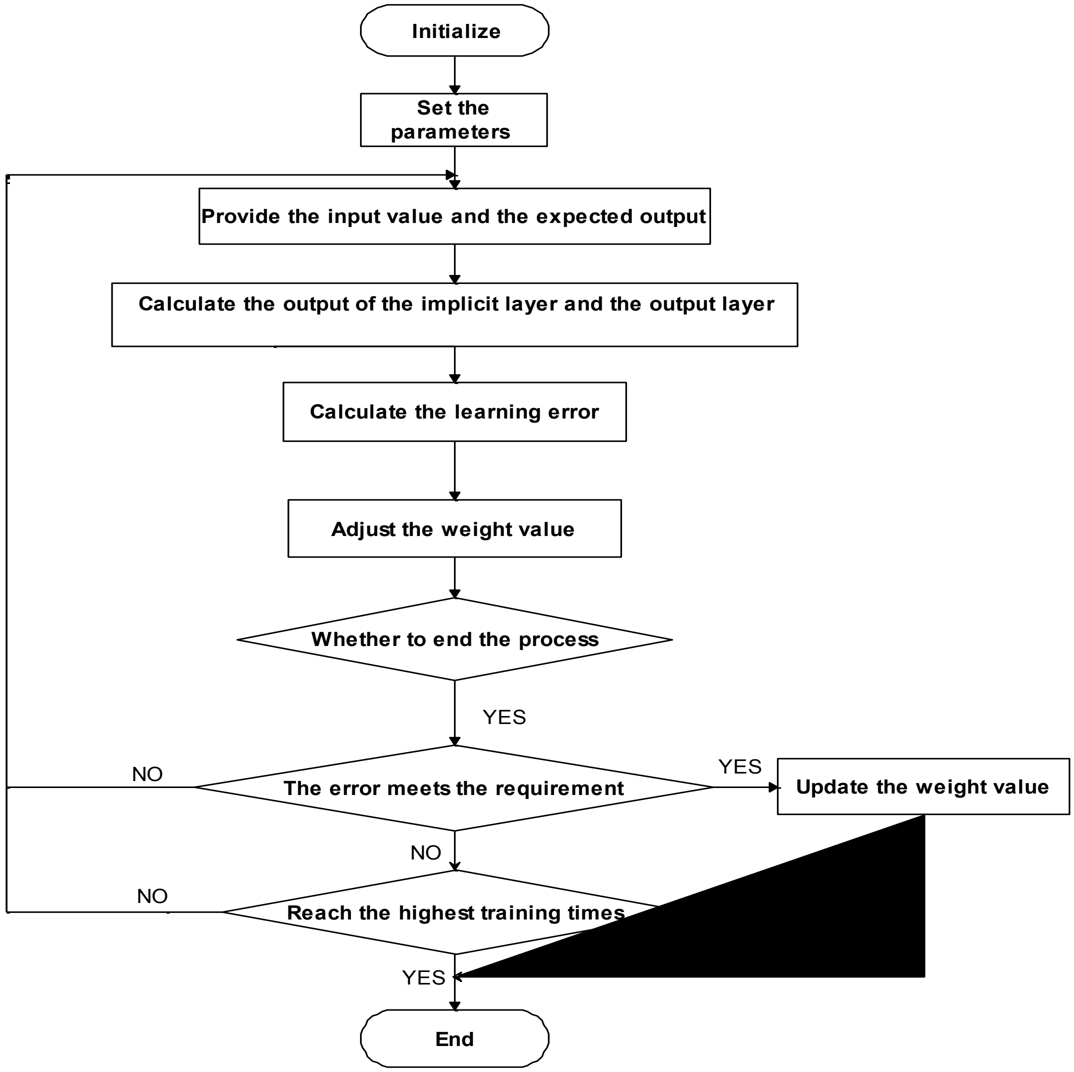

Fig. (4). BP learning training algorithm flow chart.

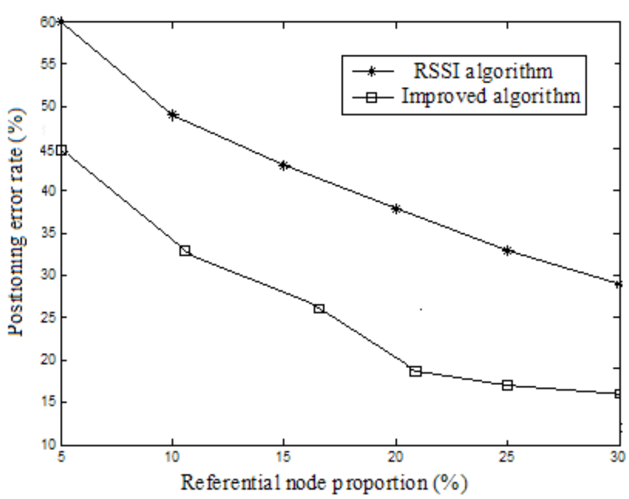

Fig. (5). The relation between the beacon node proportion and the positioning error.

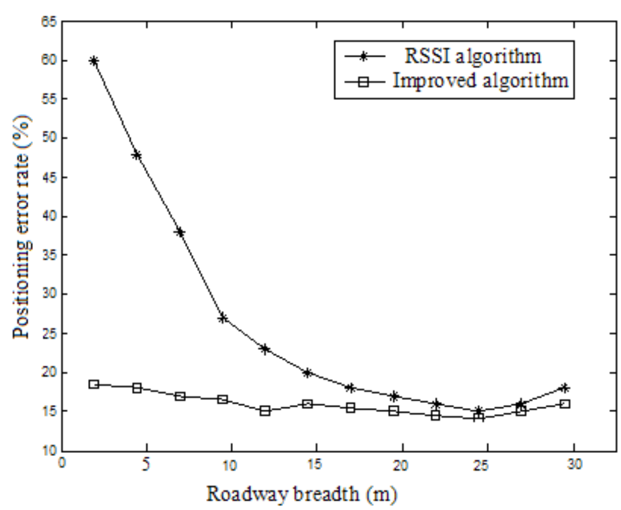

Fig. (6). Relation between the roadway breadth and the positioning error.

CONCLUSION

This paper takes the complex environment factors facing the wireless radio wave in the underground coal mine, and the vulnerability of the node transmission to attenuation thus caused, into consideration. In view of the coal mine environment, two electromagnetic transmission models, the near-field area and the far-field area, are established. Based on that, the wireless positioning algorithm is designed to improve the large error of the positioning method based on the energy. The BP algorithm is introduced for the learning training of the original algorithm. The positioning system precision is improved through the improvement of the error function of the original algorithm. The experiment results show that the error rate of the improved algorithm in this paper is smaller than that before the improvement, thus the positioning precision is significantly improved.

CONFLICT OF INTEREST

The author confirms that this article content has no conflict of interest.

ACKNOWLEDGEMENTS

Declared none.

REFERENCES

[1] Saleh, A.; Mounir, G. A joint TOA/AOA constrained minimization method for locating wireless devices in NLOS environment. *IEEE Trans. VT.*, **2009**, *58*(1), 468-472.

[2] Xiao-wei, B. *Research on Wireless Localization Technology*. Thesis Submitted to Chongqing Universityin Partial Fulfillment of the Requirement for the Degree of Master of Engineering, 2011.

[3] Xiaolei, G.; Ning Y.U.; Yinfeng, W.U. Application of BP neural network to 3D localization in wireless sensor networks. *High Technol. Lett*., **2011**, *1*(5), 471-477.

[4] Junying, M.; Jiaomin, L.; Yongzheng L.; Juan W. Study on multi-target tracking based on particle filter algorithm. *Res. J. Appl. Sci. Eng. Technol.;* **2013**, *5*(2), 427-432.

[5] Nazir, M.; Bennis, M. Learning based mechanisms for interference mitigation in self-organized femtocell networks. *45th IEEE Asilomar Conference on Signals, Systems and Computers,* **2010**, 1886-1890.

[6] Dzulkifli, M.R.; Kamarudin, M.R.; Abdul R.T. Spectrum Occupancy at UHF TV Band for Cognitive Radio Applications. *IEEE Int. RF Microw. Conf. (RFM*), **2011**, 111-114.

[7] Ren W.; Lianming, X.U.; Dejun, C.H.U. Positioning algorithm using maximum likelihood estimation of RSSI difference in wireless sensor networks. *J. Data Acquis. Process*., **2009**, *24*(6), 757-761.

[8] *Standardization Administration of the PRC, Statistical Processing and Explanation of GB/T 4883-2008.* Data. China Standardization Press, **2008**.

[9] Baykas, T.; Kasslin, M.; Cummings, M. Developing a standard for tv white space coexistence:technical challenges and solution approaches. *IEEE Wireless Commun.*, **2012**, *19*(1), 10-22.

[10] Chengpei, T.; Jiao, Y. A localization algorithm of weighted maximum likelihood estimation for wireless sensor network. *J. Inf. Comput. Sci*., **2011**, *8*(16), 4293-4300.

Received: January 6, 2015 Revised: May 20, 2015 Accepted: June 19, 2015