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Wireless location algorithm using digital broadcasting signals based on neural network

Ke Wei[1,2] Wu Lenan [1] Yin Kuixi[2]

([1] School of Information Science and Engineering, Southeast University, Nanjing 210096, China)
([2] School of Physics and Technology, Nanjing Normal University, Nanjing 210097, China)

Abstract: In order to enhance the accuracy and reliability of wireless location under non-line-of-sight (NLOS) environments, a novel neural network (NN) location approach using the digital broadcasting signals is presented. By the learning ability of the NN and the closely approximate unknown function to any degree of desired accuracy, the input-output mapping relationship between coordinates and the measurement data of time of arrival (TOA) and time difference of arrival (TDOA) is established. A real-time learning algorithm based on the extended Kalman filter (EKF) is used to train the multilayer perceptron (MLP) network by treating the linkweights of a network as the states of the nonlinear dynamic system. Since the EKF-based learning algorithm approximately gives the minimum variance estimate of the linkweights, the convergence is improved in comparison with the backwards error propagation (BP) algorithm. Numerical results illustrate that the proposed algorithm can achieve enhanced accuracy, and the performance of the algorithm is better than that of the BP-based NN algorithm and the least squares (LS) algorithm in the NLOS environments. Moreover, this location method does not depend on a particular distribution of the NLOS error and does not need line-of-sight (LOS) or NLOS identification.

Key words: digital broadcasting signals; neural network; extended Kalman filter (EKF); backwards error propagation algorithm; multilayer perceptron

Wireless location technologies, which are designated to estimate the position of a mobile station(MS), have drawn much attention for various potential location-based services[1-2]. Besides the satellite navigation systems, new alternative position location systems were proposed based on other wireless communication systems, such as cellular networks and wireless local area networks (WLAN)[3-4]. An order issued by the U. S. Federal Communications Commission (FCC) in July, 1996 requires that all the wireless service providers, including cellular and broadband wireless, provide location information to emergency 911 (E-911) public safety services. These FCC requirements have also boosted research in wireless location techniques.

Recently, digital broadcasting, such as digital video broadcasting (DVB), digital audio broadcasting (DAB), and the ATSC digital television (DTV), has been widely used as a novel information transmission technique. The positioning system using television synchronization signals was first proposed in Ref. [5]. The major advantage of the television positioning approach is from the low RF frequency, the wide band, the high transmission power and the broad coverage of DTV transmitters. Based on LOS assumptions between the transmitter and the receiver, the research in Ref. [5] showed that the location accuracy can reach meter-scale with the ATSC DTV signals. However, in urban or indoor environments location estimates are often contaminated by interference due to NLOS propagation. Therefore, the received signal parameter is a very complex function of the distance, the geometry, and the materials. The complexity of the inverse problem (i. e., to derive the position from the signals) and the lack of complete information in different environments motivate us to consider flexible models based on machine learning. The machine learning method avoids the complexity of determining a proper propagation model by traditional geometric or statistical approaches and also avoids the inference problem to derive locations from models. Several geo-location algorithms based on neural networks were presented in Refs. [6 – 7], which employed NNs as universal approximators in the sense that they can approximate any input-output mapping to any desired degree of approximation given a sufficient number of hidden units. However, the efficiency of NN depends on the network structure and the training algorithm. The conventional backward propagation (BP) algorithm is a first-order steepest descent (SD) method; it iteratively adjusts the linkweights to minimize the differences between the outputs of the NN and the desired outputs. However, the convergence speed is slow and may not be effective for predicting nonstationary processes [8]. Another learning algorithm for the solution of a nonlinear optimization problem is the Newton's method. In comparison with the BP method, this algorithm converges in fewer iterations; however, it suffers from excessive computational requirements for each pattern and is not suitable for large problems.

In this paper, the extended Kalman filter (EKF) is used to train the MLP network by treating the weights of a network as the states of a nonlinear dynamic system. Since the EKF is a second-order learning algorithm, fast convergence is expected. Furthermore, because no tuning parameters that crucially govern the convergence properties are needed; it is easier to use.

1 Measurement Model

For simplification, we consider the location in a two-dimensional (2-D) plane. The extension to a three-dimensional (3-D) space can also be done with the same steps de-

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Biographies: Ke Wei(1976—), male, graduate; Wu Lenan(corresponding author), male, doctor, professor, wuln@seu. edu. cn.

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scribed as below. The TOA method measures the range between each base station (BS) and the MS to be located. Consider an MS located nearby M BSs. For measurements at the MS from the i-th BS, the range equation can be expressed as

$$\mathrm{TOA}_i \triangleq l_i = u_i + b_i + n_i \qquad i = 1, 2, \ldots, M \tag{1}$$

where

$$u_i = \sqrt{(x_s - x_i)^2 + (y_s - y_i)^2} \qquad i = 1, 2, \ldots, M \tag{2}$$

is the true range between each BS and the MS; $X = (x, y)$ is the MS position to be estimated; b_i represents the NLOS bias, and n_i is the measurement noise which is a zero-mean random process with standard deviation σ_i. (x_s, y_s) is the true MS location and (x_i, y_i) is the i-th BS location. Since the NLOS causes the signal to arrive from a path that is longer than the true distance, then $b_i \geqslant 0$. If the measured ranges including NLOS bias are represented as l_i, the expected LOS measure ranges denoted as r_i can be written in terms of the measured ranges as

$$r_i = u_i + n_i \qquad i = 1, 2, \ldots, M \tag{3}$$

A TDOA measurement can also be separated into the true value, the NLOS error, and the receiver noise parts, as in the following equation:

$$\begin{aligned} \mathrm{TDOA}_{i,k} &= \mathrm{TOA}_i - \mathrm{TOA}_k = \\ &(u_i - u_k) + (b_i - b_k) + (n_i - n_k) \triangleq \\ &\mathrm{TDOA}^0_{i,k} + b^0_{i,k} + n^0_{i,k} \end{aligned} \tag{4}$$

where $\mathrm{TDOA}^0_{i,k}$ is the true distance difference; $b^0_{i,k}$ represents the NLOS bias; and $n^0_{i,k}$ is the measurement noise which is a zero-mean random process with standard deviation $\sigma_{i,k}$.

2 EKF Algorithm for NN Training

2.1 Multilayer perceptron

An MLP consists of several layers of nodes which express artificial neural units. Each node connected by the links with all the nodes in the adjacent layer computes a weighted sum of inputs, and then adds an offset to the sum. The computed result is the output through a nonlinear function. The three-layer structure MLP scheme for wireless location described here is illustrated in Fig. 1. In this paper, the least number input measurements, i. e., three TOAs and two TDOAs are employed to estimate MS location, and the network shown has only one hidden layer, which is based on the fact that the small-size NN would be preferable to require a shorter time for both training and actual position estimations. The outputs of the MLP are x and y coordinates of the corresponding position as shown in Fig. 1.

Let the i-th node in the n-th layer be denoted by the node (n, i); $x^n_i(t)$ is the output of the node (n, i) for pattern t, and $x_i(t)$ stands for the i-th element for pattern t. The linkweight from the node (n, j) to the node $(n+1, i)$ and the offset of the node (n, i) are expressed as $a^n_{i,j}$ and θ^n_i, respectively.

In our network, each node in the input layer is assumed to perform no operation, that is

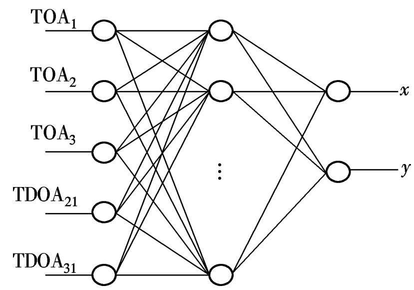

Fig. 1 Structure of multilayered neural network for wireless positioning

$$x^1_i(t) = x_i(t) \qquad 1 \leqslant i \leqslant N_1 - 1 \tag{5}$$

Furthermore, the offset is treated as the linkweight by putting

$$x^n_{N_n}(t) = 1 \qquad 1 \leqslant n \leqslant S \tag{6}$$

$$a^n_{i,N_n} = \theta^{n+1}_i \qquad 1 \leqslant n \leqslant S-1; 1 \leqslant i \leqslant N_{n+1} - 1 \tag{7}$$

where N_n stands for the total number of nodes in the n-th layer, and S represents the total number of layers including the input and output layers. As shown in Fig. 2, the operation of the node $(n+1, i)$ is then characterized by

$$x^{n+1}_i(t) = f\left(\sum_{j=1}^{N_n-1} a^n_{i,j}\, x^n_j(t) + \theta^{n+1}_i\right) = f\left(\sum_{j=1}^{N_n} a^n_{i,j}\, x^n_j(t)\right) \tag{8}$$

The function $f(\cdot)$ is usually given by the following sigmoid function:

$$f(x) = \frac{1}{1 + \mathrm{e}^{-x}} \tag{9}$$

This is because the derivative of $f(x)$ is easily obtained by

$$f'(x) = f(x)(1 - f(x)) \tag{10}$$

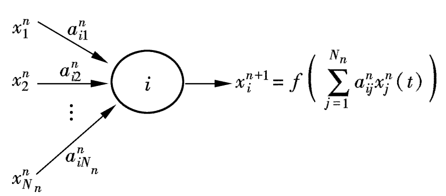

Fig. 2 Operations of the node $(n+1, i)$

2.2 Extended Kalman filtering training algorithm

The conventional BP algorithm iteratively adjusts the linkweights using the SD technique so that the differences between the outputs of the MLP and the desired outputs are minimized. However, the convergence speed is inherently slow because the learning rate is fixed. Furthermore, we have to tune the learning rate and the momentum term in a heuristic manner so that a quick convergence is obtained. An improper choice of these parameters may cause problems of unstability or suffer from much slower convergence. The advent of a more powerful learning algorithm instead of the SD-based algorithm has been expected. Using the EKF for updating the weights of an MLP can result in faster convergence in the sense that fewer training iterations are needed.

Since the connection weight vector can be viewed as the state of a static nonlinear dynamic system, we set the unknown linkweights as the state vector,

$$\boldsymbol{a} = [(\boldsymbol{a}^1)^{\mathrm{T}}, (\boldsymbol{a}^2)^{\mathrm{T}}, \ldots, (\boldsymbol{a}^{S-1})^{\mathrm{T}}]^{\mathrm{T}} \tag{11}$$

where

$$\boldsymbol{a}^n = [(\boldsymbol{a}_1^n)^{\mathrm{T}}, (\boldsymbol{a}_2^n)^{\mathrm{T}}, \ldots, (\boldsymbol{a}_{N_{n+1}-1}^n)^{\mathrm{T}}]^{\mathrm{T}} \tag{12}$$

$$\boldsymbol{a}_i^n = [a_{i,1}^n, a_{i,2}^n, \ldots, a_{i,N_n}^n]^{\mathrm{T}} \tag{13}$$

Let the output vector of the nodes in the n-th layer and the desired output vector of the MLP be

$$\boldsymbol{x}^n(t) = [x_1^n(t), x_2^n(t), \ldots, x_{N_n}^n(t)]^{\mathrm{T}} \tag{14}$$

and

$$\boldsymbol{d}(t) = [d_1(t), d_2(t), \ldots, d_{N_s}(t)]^{\mathrm{T}} \tag{15}$$

respectively. In Eq. (15), $d_i(t)$ is the desired output of the i-th node in the output layer for pattern t. The MLP is then expressed by the following nonlinear system equations:

$$\boldsymbol{a}(t+1) = \boldsymbol{a}(t) \tag{16}$$

$$\boldsymbol{d}(t) = \boldsymbol{h}_t(\boldsymbol{a}(t)) + \boldsymbol{v}(t) = \boldsymbol{x}^S(t) + \boldsymbol{v}(t) \tag{17}$$

where $\boldsymbol{x}^S(t)$ is the output vector of the nodes in the output layer for pattern t. The input to the MLP for pattern t combined with the structure of the MLP is expressed by a nonlinear time-variant function $\boldsymbol{h}_t$. The observation vector is represented by the desired output vector $\boldsymbol{d}(t)$, and $\boldsymbol{v}(t)$ is assumed to be a white noise vector with covariance matrix $\boldsymbol{R}(t)$ which is regarded as a modeling error.

Using the standard EKF method [9] to solve Eqs. (16) and (17), we obtain the following real-time learning algorithm:

$$\hat{\boldsymbol{a}}(t) = \hat{\boldsymbol{a}}(t-1) + \boldsymbol{K}(t)[\boldsymbol{d}(t) - \hat{\boldsymbol{x}}^S(t)] \tag{18}$$

$$\boldsymbol{K}(t) = \boldsymbol{P}(t-1)\boldsymbol{H}(t)^{\mathrm{T}}[\boldsymbol{H}(t)\boldsymbol{P}(t-1)\boldsymbol{H}(t)^{\mathrm{T}} + \boldsymbol{R}(t)]^{-1} \tag{19}$$

$$\boldsymbol{P}(t) = \boldsymbol{P}(t-1) - \boldsymbol{K}(t)\boldsymbol{H}(t)\boldsymbol{P}(t-1) \tag{20}$$

We set $\boldsymbol{P}(t) = \boldsymbol{P}(t \mid t)$ and $\hat{\boldsymbol{a}}(t) = \hat{\boldsymbol{a}}(t \mid t)$, since $\boldsymbol{P}(t \mid t) = \boldsymbol{P}(t+1 \mid t)$ and $\hat{\boldsymbol{a}}(t \mid t) = \hat{\boldsymbol{a}}(t+1 \mid t)$. Also $\hat{\boldsymbol{x}}^S(t)$ denotes the estimate of $\boldsymbol{x}^S(t)$ based on the observations up to time $t-1$, which is computed by $\hat{\boldsymbol{x}}^S(t) = \boldsymbol{h}_t(\hat{\boldsymbol{a}}(t-1))$. $\boldsymbol{H}(t)$ is expressed as

$$\boldsymbol{H}(t) = \left(\frac{\partial \boldsymbol{x}^S(t)}{\partial \boldsymbol{a}}\right)\Bigg|_{a=\hat{\boldsymbol{a}}(t-1)} \tag{21}$$

As each new pattern is available, using Eqs. (18) to (21), we can approximately compute the minimum variance estimate of the linkweights which is asymptotically equivalent to the least squares estimate.

3 Simulation Results and Performance Analysis

Simulation results are provided in this section to assess the performance of the proposed algorithm. We assume that the MS can receive the signals from at least three BSs all the time and all the clocks of participating BSs and MS are synchronized. Considering the long distance between broadcasting transmitter towers, the coordinates of BSs are set as (0 m, 0 m), (5 000 m, 5 000 m) and (10 000 m, 0 m). We assume that the variances of all the TOA measurement noises are the same; i. e., they are modeled as random variables with zero mean and variance 30 m, whereas the NLOS measurement noise is also assumed to be a white random variable but with positive mean m_{NLOS} = 513 m, and the standard deviation σ_{NLOS} = 409 m[10]. Since a small-size MLP is usually required, the number of neurons in the hidden layer is fixed as 20 only in our simulation experiments. The MS is placed in uniform random locations in the coverage region of three BSs so that we can choose 2 000 MS positions. The training phase uses 1 000 MS positions and the other 1 000 MS positions are used in the test phase to estimate the position error. The NN approach using the BP algorithm for geo-location in Ref. [6] is chosen to compare our method and the traditional LS algorithm.

Compared with the FCC requirements, i. e., 67% location error at 100 m and 95% location error at 300 m, Tab. 1 shows the root square error (RSE) of the three algorithms in four different cases under this condition. The RSE is defined as

$$\mathrm{RSE} = \sqrt{[(x_k - x_s)^2 + (y_k - y_s)^2]} \tag{22}$$

Tab. 1 Performance comparison among three algorithms m

Situation	EKF-NN		BP-NN		LS	
	67%	95%	67%	95%	67%	95%
0LOS, 3NLOS	80. 05	192. 10	155. 11	250. 90	280. 73	447. 81
1LOS, 2NLOS	71. 95	169. 58	128. 90	215. 69	273. 11	427. 33
2LOS, 1NLOS	62. 69	133. 19	111. 67	189. 51	253. 33	399. 81
3LOS, 0NLOS	51. 21	95. 82	58. 18	99. 23	40. 55	71. 08

It can be seen from Tab. 1 that the LS algorithm is superior to the NN algorithm under LOS environments, but inferior under NLOS environments. The EKF-based NN method achieves the least RSE among all the three methods, and the BP-NN and the LS algorithms cannot meet the FCC requirements even if there is only one NLOS BS. Even in the worst case, i. e., when the three BSs are all in NLOS condition, the proposed method has a performance of 67% error at 80. 05 m and 95% location error at 192. 10 m, which is still below the location error mandated by the FCC.

Fig. 3 shows the error cumulative distribution function of different algorithms, where the three BSs are all in NLOS condition. Corresponding to Tab. 1, it can be observed from Fig. 3 that although the BP-NN method improves the accuracy of the location estimation compared with the traditional LS algorithm, it is still inferior to the EKF-NN in the NLOS situation. Fig. 4 shows the relationship between the RSE error and the number of training times. It can be seen that the error of the EKF-based algorithm decreases rapidly to reach a convergence value of about 80 m using approximately 60 training times, while the BP-based algorithm attains about 200 m after 120 training times. Due to this, a great improvement in the accuracy of the location estimation using the EKF-NN method is obtained.

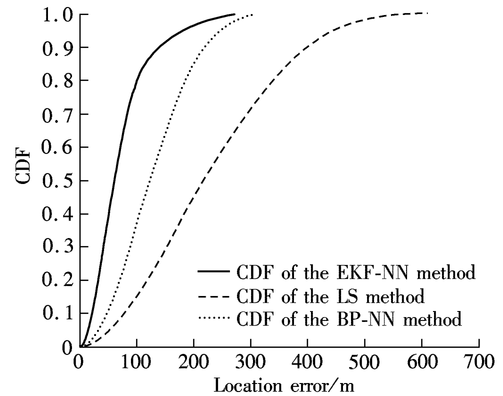

Fig. 3 The CDF of location error

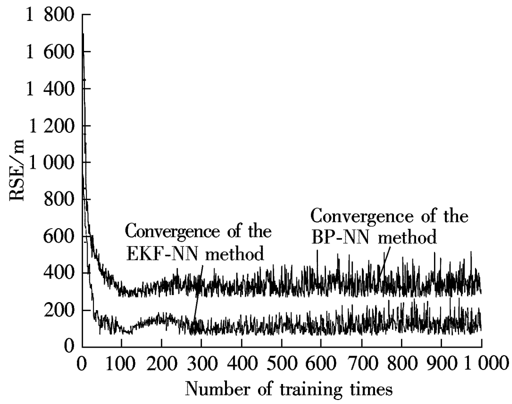

Fig. 4 Contrast of convergence between EKF and BP algorithm

In the real situation, NLOS errors depend on the propagation environments and change from time to time. NLOS errors are obtained as the excessive delay multiplied by the speed of light. In order to illuminate the performance in real environments, NLOS errors in the second case are assumed to be exponential distributions according to the COST 259 channel model under urban, bad urban, rural, and suburban environments[11-12]. COST 259 is a European research initiative in the field of "flexible personalized wireless communications," which is detailed enough to reflect all the relevant properties of propagation channels and allow rapid implementation for short simulation times.

Fig. 5 shows the performance on root mean square error (RMSE) location error of three algorithms under different environments. We define the RMSE position error shown as

$$\mathrm{RMSE} = \sqrt{\frac{1}{L}\sum_{m=1}^{L}[(x_{k,m}-x_s)^2+(y_{k,m}-y_s)^2]} \quad (23)$$

All the RMSE location errors are obtained from the average of $L = 1\ 000$ independent runs with the same parameters. The figure contains four groups of bar plots, and each group corresponds to one of four environment types. Within a group, the RMSE values derived from the three algorithms are represented by the heights of three bars.

On the whole, the performance ranking from the worst to the best with respect to the environment types are: bad urban, urban, suburban, and rural. As shown in Fig. 5, the RMSE values of the proposed algorithm are smaller than the results of the LS and the BP-NN algorithms in all of the scenarios, which convinces us that the proposed method can adapt well to real environments and gives a good estimation of the location of the MS. Compared with the BP-based and the LS-based algorithms, the RMSE of location errors is improved approximately from 200 to 350 m in an urban environment, and in a bad urban environment, the improvement even goes up to about 300 to 500 m. For a suburban environment, the improvement is around 50 to 150 m; as for a rural environment, in which NLOS errors are not severe and do not leave much space for improvement, the performance improvement of the RMSE value is not very visible.

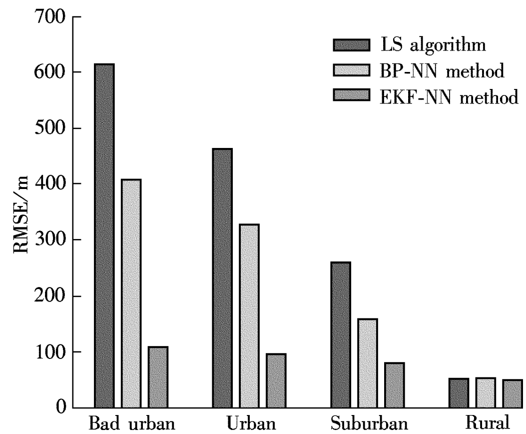

Fig. 5 RMSE location error of three algorithms under different environments

4 Conclusion

The characteristics of higher power levels, wider bandwidths, and lower frequencies in the digital broadcasting positioning system make it possible to operate very well in different environments. This paper proposes an efficient and practical neural network method that performs nonlinear mapping between the measured TOAs and TDOAs from nearby BSs and the MS location. The EKF is well known as a state estimation method for a nonlinear system and can be used as a parameter estimation method by augmenting the state with unknown parameters. A multilayered NN is a nonlinear system having a layered structure, and its learning algorithm is regarded as parameter estimation for such a nonlinear system. Analytical results of accuracy show that the EKF-based scheme has the advantages of robustness and being easy for training and on-line implementation. Simulation results demonstrate that the proposed algorithm provides a better accuracy location than the other two methods. Moreover, it does not require any statistical distribution knowledge of the NLOS error or LOS/NLOS identification. The results encourage further investigation into the impact of the number of input variables, hidden neurons, and the types of activation functions used.

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基于神经网络的数字广播信号无线定位算法

柯 炜[1,2] 吴乐南[1] 殷奎喜[2]

([1] 东南大学信息科学与工程学院,南京 210096)

([2] 南京师范大学物理科学与技术学院,南京 210097)

摘要:为了提高非视距(NLOS)环境下无线定位的准确性和可靠性,提出了一种利用数字广播信号进行移动台定位的神经网络方法. 该方法利用神经网络的学习特性和逼近任意非线性函数的能力,建立到达时间(TOA)和到达时间差(TDOA)测量数据与坐标之间的映射关系. 将神经网络的连接权值作为非线性动态系统的状态量进行估计,用基于扩展卡尔曼(EKF)的实时神经网络训练算法来训练多层感知器网络. 由于基于 EKF 的训练算法给出的是连接权值的近似最小方差估计,其收敛性要优于误差反向传播(BP)算法. 仿真结果表明,该算法在 NLOS 环境下有较高的定位精度,性能优于 BP 基的神经网络算法和最小二乘算法;且该定位方法不依赖于特定的 NLOS 误差分布,也无需视距(LOS)和非视距识别.

关键词:数字广播信号;神经网络;扩展卡尔曼滤波;误差反向传播算法;多层感知器

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