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A Taylor Based Localization Algorithm for Wireless Sensor Network Using Extreme Learning Machine

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SUMMARY More recently, there has been a growing interest in the study of wireless sensor network (WSN) technologies for Interest of Things (IoT). To improve the positioning accuracy of mobile station under the nonline-of-sight (NLOS) environment, a localization algorithm based on the single-hidden layer feedforward network (SLFN) using extreme learning machine (ELM) for WSN is proposed in this paper. Optimal reduction in the time difference of arrival (TDOA) measurement error is achieved using SLFN optimized by ELM. Compared with those traditional learning algorithms, ELM has its unique feature of a higher generalization capability at a much faster learning speed. After utilizing the ELM by randomly assigning the parameters of hidden nodes in the SLFN, the competitive performance can be obtained on the optimization task for TDOA measurement error. Then, based on that result, Taylor algorithm is implemented to deal with the position problem of mobile station. Experimental results show that the effect of NLOS propagation is reduced based on our proposed algorithm by introducing the ELM into Taylor algorithm. Moreover, in the simulation, the proposed approach, called Taylor-ELM, provides better performance compared with some traditional algorithms, such as least squares, Taylor, backpropagation neural network based Taylor, and Chan positioning methods

key words: wireless sensor network, time difference of arrival, extreme learning machine, non-line-of-sight

1. Introduction

As a new method used to obtain and process information, wireless sensor network (WSN) is one of the most important technologies in the 21st century. Specially, it plays an important role in the research and development of Internet of Things (IoT). From the application side, WSN has demonstrated many successful applications across a wide range of domains, such as target tracking, space exploration, environment monitoring, and so on [1], [2]. WSN is composed of large number of sensor nodes which have a tiny physical structure, low power consumption, and low price. These nodes have the capabilities of communication, sensing, and computing [3]. In the practical applications of WSN, the localization techniques play an important role. Sometimes,

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WSN is unavailable without knowing the location of monitoring information [4]. Generally speaking, the manned localization is a complicated process and might be influenced by multiple factors, e.g., the power, the cost, the circumstance, and so on. Therefore recent years have witnessed a growing interest in the study of node positioning technologies in WSN.

The performance requirements of localization for WSN include expansibility, accuracy, reliability, and low energy consumption. Among the available localization algorithms, the time difference of arrival (TDOA) algorithm has been a long-term focus, because it does not require strict time synchronization between the mobile station (MS) and base station (BS) [5]. There are some typical implementation methods for TDOA localization, e.g., Taylor series expansion algorithm [6], Chan algorithm [7], and least squares (LS) algorithm [8]. Chan algorithm has good accuracy when the TDOA measurement error is small and it is an ideal zeromean Gaussian random variable. However when the TDOA measurement error is large in the non-line-of-sight (NLOS) environment, the performance of Chan algorithm will be severely affected. LS algorithm does not need to take the statistical property of errors under NLOS environment into consideration, thus the positioning accuracy of this algorithm is better than Chan algorithm [9]. Meanwhile Taylor series expansion algorithm should know an initial estimate close to real position to guarantee convergence of this algorithm and the performance of this algorithm is better than Chan algorithm and LS algorithm under NLOS environment [10]. But the positioning accuracy of Taylor algorithm in NLOS environment is much weaker than that in line-of-sight (LOS) environment. In order to reduce NLOS error of the TDOA measurements, several geo-location algorithms based on neural network (NN) have been presented due to the fast adaptability and approximation capabilities of NN. For instance, a location algorithm based on backpropagation (BP) NN was proposed to optimize the NLOS errors in [11]. The conventional BP NN learning algorithm is a first-order steepest decent method, and it iteratively adjusts the linkweights to minimize the differences between the outputs of the NN and the desired outputs [12]. Nevertheless, the convergence speed is relatively slow and it could fall into local minimum. Then a kind of modified NN, i.e., radial basis function (RBF) NN was used to improve the positioning accuracy [13], but RBF NN need trivial human intervene [14]. In view of this, the purpose of this paper is to obtain high quality solutions to reduce the NLOS error of

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TDOA measurements, based on a proposed single-hidden layer feedforward network (SLFN) using extreme learning machine (ELM) which provides a higher generalization capability at a much faster learning speed and with least human intervene.

Specifically, the SLFN based on ELM learning algorithm is used to approximate the nonlinear continuous rational function to reduce NLOS errors. Here ELM is a very simple learning algorithm with a faster learning speed compared with many learning algorithms, and it tends to reach the solutions straightforward without facing such trivial issues like local minima, improper learning rate, overfitting, poor computational scalability, and so on [15]. More recently, there has been a tremendous surge of interest in the study of ELM, since it overcomes some challenges faced by other computational intelligence techniques. The essence of this paper is to develop SLFN using ELM to correct NLOS errors of the TDOA measurement. Finally, with the solutions obtained by using the above approach, the location result is achieved via Taylor series expansion algorithm. This algorithm can achieve a higher positioning accuracy in NLOS environment with extremely fast speed.

This paper is organized as follows. The TDOA measurement error model and SLFN using ELM is presented in Sect. 2. A Taylor based localization algorithm using ELM is proposed in Sect. 3. Simulation results and discussions are presented in Sect. 4. Finally, conclusions are given in Sect. 5.

2. Model Description

2.1 TDOA Measurement Error Model

In real environment, TDOA measurement error can be caused by multipath, NLOS, multiple access interference, and the precision of testing equipment [16].

There are *N* BSs, namely, BS_1 , BS_2 , ..., BS_N . A TDOA measurement consists of the true value, the additional delay error caused by NLOS, and the systematic measurement error, defined as follows [17]:

$$TDOA_{i1} = TOA_i - TOA_1 = TDOA_{i1}^* + \eta_{i1} + \tau_{NLOS_{i1}}, i = 2, 3, \dots, N \quad (1)$$

where TOA_i is the measurement of time on arrival (TOA) between the MS and the BS_i , $TDOA_{i1}^*$ is the true distance difference between BS_i and BS_1 , η_{i1} is the systematic measurement error between BS_i and BS_1 and η_{i1} is a zero-mean Gaussian distribution with standard deviation $\sigma_{\eta_{i1}}$, $\tau_{NLOS_{i1}}$ represents the NLOS bias between BS_i and BS_1 and these $\tau_{NLOS_{i1}}$ are mutually exclusive.

In different signal path, the NLOS error may follow exponential distribution, uniform distribution or delta distribution. This paper takes exponential distribution for example and its probability density function is designed as:

$$f(\tau_{NLOS}) = \begin{cases} \frac{1}{\tau_{RMS}} \exp(-\frac{\tau_{NLOS}}{\tau_{RMS}}), & \tau_{NLOS} > 0\\ 0, & \tau_{NLOS} \le 0 \end{cases}$$
(2)

 Table 1
 Some parameters in different channels.

Environment	T_1 (μ s)	ε	$\sigma_{\xi} (dB)$
Downtown	1.0	0.5	4
Urban	0.4	0.5	4
Suburb	0.3	0.5	4
Rural	0.1	0.5	4
Mountain	0.1	0.5	4



Fig. 1 The SLFN model based on ELM used to reduce the TDOA measurement errors.

where τ_{RMS} is the root mean square (RMS) of delay spread (μ s), and it can be given as:

$$\tau_{RMS} = T_1 d_i^{\varepsilon} \xi \tag{3}$$

where T_1 (μ s) is the medians of τ_{RMS} when d_i equals 1 km, d_i (km) is the distance between MS and BS_i , ε is a constant ranging from 0.5 to 1, ξ is a zero-mean logarithmic normal distribution with standard deviation σ_{ξ} ranging from 4 dB to 6 dB [18]. Under different signal path some parameters are listed in Table 1.

2.2 SLFN Based on ELM

Figure 1 shows a SLFN model based on ELM, which is used to reduce errors of TDOA measurements provided by BSs. This NN architecture is composed of three parts, i.e., input layer, hidden layer, and output layer.

In the input layer of Fig. 1, the input vector includes m TDOA measurements obtained from m + 1 BSs, and it can be expressed as follows:

$$x_{j} = \left[TDOA_{21}^{j}, TDOA_{31}^{j}, \cdots, TDOA_{m+1,1}^{j} \right].$$
(4)

The output is the corrected TDOA values, and it can be expressed as follows:

$$o_j = \left[r_{21}^j, r_{31}^j, \cdots, r_{n+1,1}^j \right].$$
(5)

ELM is proposed to speed up the learning process of SLFN. Specifically, ELM does not only achieve smaller training error but also the smallest norm of output weight [19]. Let *m* and *n* be the number of input nodes and output nodes, respectively. There are *K* arbitrary distinct samples (x_j, t_j) , where $x_j = [x_{j1}, x_{j2}, \cdots x_{jm}]^T \in \mathbb{R}^m$, $t_j = [t_{j1}, t_{j2}, \dots, t_{jn}]^T \in \mathbb{R}^n$, and $j = 1, \dots, K$. The standard SLFN with *L* hidden neurons can be modeled in the form of:

$$\sum_{i=1}^{L} \beta_i G(w_i, b_i, x_j) = o_j, \ j = 1, 2, \cdots, K$$
(6)

where $\beta_i = [\beta_{i1}, \beta_{i2}, \dots, \beta_{in}]^T$ is the weight vector connecting the *i*-th hidden node and the output nodes, $w_i = [w_{i1}, w_{i2}, \dots, w_{im}]^T$ is the weight vector connecting the *i*-th hidden node and the input nodes, b_i is the threshold of the *i*-th hidden nodes, $G(w_i, b_i, x_j)$ is the output of the *i*-th hidden node in terms of x_j , o_j is the actual output of this NN with input x_j [20].

For SLFN with additive hidden nodes in which the activation function is g(x), the $G(w_i, b_i, x_j)$ is given as follows:

$$G(w_i, b_i, x_j) = g(w_i \cdot x_j + b_i). \tag{7}$$

The above SLFN with *L* hidden nodes is designed to approximate these *K* samples with zero error, which means that the cost function $E = \sum_{j=1}^{K} ||o_j - t_j|| = 0$, then existing w_i , b_i , and β_i such that:

$$\sum_{i=1}^{L} \beta_i G(w_i, b_i, x_j) = t_j, \ j = 1, 2, \cdots, K.$$
(8)

The above equation can be rewritten compactly as:

$$H\beta = T \tag{9}$$

where

$$\begin{split} & H(w_1,\cdots,w_L,b_1,\cdots,b_L,x_1,\cdots,x_K) \\ & = \begin{bmatrix} G(w_1,b_1,x_1) & \cdots & G(w_L,b_L,x_1,) \\ \vdots & \dots & \vdots \\ G(w_1,b_1,x_K) & \cdots & G(w_L,b_L,x_K) \end{bmatrix}_{K\times L}, \\ & \beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{L\times n}, \quad T = \begin{bmatrix} t_1^T \\ \vdots \\ t_K^T \end{bmatrix}_{K\times n}. \end{split}$$

Here, *H* is called the hidden layer output matrix of this NN, the *i*-th column of *H* is the output of the *i*-th hidden node with respect to inputs x_1, \dots, x_K .

With these notations, Huang *et al.* proposed a theorem in [15], which stated that under the condition that activation function $g: R \to R$ is infinitely differentiable in any interval, for any w_i and b_i randomly chosen from any intervals of R^m and R, $||H_{K \times L}\beta_{L \times n} - T_{K \times n}|| < \varepsilon$, where ε is any small positive value.

Thus, unlike the most common understanding that all the parameters of SLFNs need to be adjusted, the input weight w_i and hidden layer biases b_i can be randomly assigned and remain unchanged once assigned. For fixed w_i and b_i , the training task for a SLFN is simply equivalent to finding a least-squares solution $\hat{\beta}$ of the above system $H\beta = T$:

$$|| H(w_1, \dots, w_L, b_1, \dots, b_L, x_1, \dots, x_K)\hat{\beta} - T || = \min_{\alpha} || H(w_1, \dots, w_L, b_1, \dots, b_L, x_1, \dots, x_K)\beta - T || .$$
(10)

The unique smallest norm least-squared solution of the above linear system is:

$$\hat{\beta} = H^{\dagger}T, \tag{11}$$

where H^{\dagger} is the Moore-Penrose generalized inverse of matrix H [21].

The proposed solution in the ELM algorithm, i.e., $\hat{\beta} = H^{\dagger}T$, has the following important properties [22]:

(1) It is one of the least-squares solutions to equation $H\beta=T$, which means that the smallest training error can be reached. However, most of the learning algorithm like the gradient-based learning such as BP can not reach the minimum training error due to local minimum or finite training iteration;

(2) It has the smallest norm among all the least squares solutions of the $H\beta=T$;

(3) The minimum norm least squares solution is unique and it is $\hat{\beta} = H^{\dagger}T$.

Then ELM algorithm can be summarized as follows: Give a training set $\{(x_j, t_j)|x_j \in \mathbb{R}^m, t_j \in \mathbb{R}^n, j =$

 $1, \dots, K$, the number of hidden node *L*, and activation function g(x).

(1) Randomly assign input weight vector w_i and bias b_i , $i = 1, 2, \dots, L$.

(2) Calculate the hidden layer output matrix H based on Eq. (9).

(3) Calculate the output weight $\beta = H^{\dagger}T$.

In summary, the implementation can be described as Algorithm 1.

Algorithm 1	ELM algorithm	
1: give the input of	f testing set: test_input;	

2: randomly generate a matrix *w* with *L* rows and *m* columns;

3: randomly generate a matrix *b* with *L* rows;

4: give an input vectors of training set: *x*;

- 5: H = G(w, b, x);
- 6: $\beta = H^{\dagger}T$;

7: $H_test = G(w, b, test_input);$

8: *o_test* = *H_test* × β;
9: output the result *o_test*;

3. Taylor Algorithm Based on SLFN Using ELM

3.1 Taylor Series Expansion Algorithm

Assuming that the fixed position of BS_i $(1 \le i \le N)$ is (x_i, y_i) , and the position of MS is (x, y), the distance between MS and BS_i can be defined as:

$$r_{i} = ct_{i} = \sqrt{(x_{i} - x)^{2} + (y_{i} - y)^{2}}$$

= $\sqrt{x_{i}^{2} + y_{i}^{2} - 2x_{i}x - 2y_{i}y + x^{2} + y^{2}}$ (12)

where *c* is the wave propagation velocity, t_i is the TOA measurement of BS_i .

Let r_{i1} be the distance difference between BS_i and BS_1 , then it can be designed as:

$$r_{i1} = c(t_i - t_1) = r_i - r_1$$

= $\sqrt{(x_i - x)^2 + (y_i - y)^2} - \sqrt{(x_1 - x)^2 + (y_1 - y)^2}$ (13)

where $i = 2, 3, \dots, N$.

The above Eq. (13) is a nonlinear equation related to (x, y) of MS. Usually it should be translated into linear equation, and then the result is obtained. Taylor series expansion algorithm is a representative algorithm with good positioning performance [23]. It is a recursive algorithm requiring an initial estimated location. It will gradually converge to the estimated position by getting the partial least squares solution of the TDOA measurement errors in every recursive procedure.

The first order of Taylor series expansion in (x_a, y_a) of function f can be designed as follows:

$$f(x_a + \delta_x, y_a + \delta_y) = f(x_a, y_a) + \delta_x \frac{\partial f(x_a, y_a)}{\partial x} + \delta_y \frac{\partial f(x_a, y_a)}{\partial y} + T$$
(14)

where *T* is the remainder of the Taylor series expansion, $(x_a + \delta_x, y_a + \delta_y)$ is the neighborhood of point (x_a, y_a) .

Substituting Eq. (13) into the initial estimated location (x_0, y_0) , we get the first order of Taylor series expansion in the form of [24]:

$$\psi = h - G\delta. \tag{15}$$

In the above equation, ψ is the error vector, and

$$h = \begin{bmatrix} R_{21} - r_2 + r_1 \\ R_{31} - r_3 + r_1 \\ \vdots \\ R_{N1} - r_N + r_1 \end{bmatrix}, \quad \delta = \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix},$$

$$G = \begin{bmatrix} \frac{x_1 - x_0}{r_1} - \frac{x_2 - x_0}{r_3} & \frac{y_1 - y_0}{r_1} - \frac{y_2 - y_0}{r_2} \\ \frac{x_1 - x_0}{r_1} - \frac{x_2 - x_0}{r_3} & \frac{y_1 - y_0}{r_1} - \frac{y_3 - y_0}{r_3} \\ \vdots & \vdots \\ \frac{x_1 - x_0}{r_1} - \frac{x_N - x_0}{r_N} & \frac{y_1 - y_0}{r_1} - \frac{y_N - y_0}{r_N} \end{bmatrix}$$

where $r_i (1 \le i \le N)$ appeared in above *G* and *h* is the distance between initial estimated location (x_0, y_0) and BS_i , and it can be obtained by setting $x = x_0$ and $y = y_0$ in Eq. (12), $R_{i1} (1 \le i \le N)$ in above *h* are the TDOA measurements provided by the BSs.

The result of δ in Eq. (15) can be obtained by using weighted least squares (WLS) algorithm:

$$\delta = \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} = (G^T Q^{-1} G)^{-1} G^T Q^{-1} h \tag{16}$$

where Q is the covariance matrix of the TDOA measurements.

In the next recursion process, we assume that $x_0 = x_0 + \Delta x$, $y_0 = y_0 + \Delta y$, respectively. Repeating the above process until Δx and Δy are small enough [25], and the following

threshold ε could be met:

$$\Delta x | + |\Delta y| < \varepsilon. \tag{17}$$

Then, the position (x_0, y_0) is the estimated location of MS.

3.2 Taylor Algorithm Based on SLFN Using ELM

Taylor algorithm has a high accuracy in LOS environment. However, the performance will be greatly affected under NLOS environment. This paper uses SLFN based on ELM to reduce the NLOS error of TDOA measurement, and the estimate position of MS can be obtained via Taylor algorithm. The proposed method can effectively improve the positioning accuracy. The detailed steps are as follows:

(1) It is assumed that *D* groups of TDOA measurements, i.e., $a_j (1 \le j \le D)$, are obtained in NLOS environment. Then SLFN based on ELM is constructed and trained. Here, the target sample vectors of the network, i.e., $z_j (1 \le j \le D)$, are the TDOA values that does not contain the NLOS error, which can be obtained based on the actual distances from each MS to all the BSs.

(2) Reduce the NLOS error of TDOA measurement via the trained SLFN using ELM.

(3) Use Taylor algorithm with modified TDOA values to estimate the location of MS.

The implementation can be also described as Algorithm 2. Specifically, we call it algorithm Taylor-ELM.

Algorithm 2	Taylor-ELM algorithm
Input:	
The TDOA me	asurements provided by N BSs under NLOS environ-
ment, i.e., TDO	$A_{21}, TDOA_{31}, \cdots, TDOA_{N1};$
Output:	
The estimated le	ocation of MS: EP;
1: give a training s	set $\Xi = \{(a_j, z_j) 1 \leq j \leq D\}$ that will be trained based
on SLFN using	ELM described in Algorithm 1;
2: $\beta = H^{\dagger}(w_1, \cdots, w_n)$	$(b_L, b_1, \cdots, b_L, a_1, \cdots, a_D)T, T = [z_1, \cdots, z_D]^T;$
3: $y_{test} = [R_{21}, \cdot$	$\cdots, R_{N1}] = H(w_1, \cdots, w_L, b_1, \cdots, b_L, x_test)\beta, x_test =$
$[TDOA_{21}, \cdots, T]$	$[TDOA_{N1}]^T;$
4: set initial estimation	ated position: <i>IEP</i> ;
5: repeat	
6: for $1 \le i \le N$	' do
7: $R_i = \text{distar}$	nce $((x_i, y_i), IEP);$
8: end for	
9: for $2 \le i \le N$	' do
10: $h(i-1) =$	$R_{i1}-(R_i-R_1);$
11: end for	
12: $\delta = (\delta_1, \delta_2)^T$	$= (G^{I} Q^{-1} G)^{-1} G^{I} Q^{-1} h^{I};$
13: EP = IEP +	δ^{\prime} ;
14: $IEP = EP;$	

15: **until**
$$(\delta_1 + \delta_2 < \varepsilon)$$

4. Simulation Results and Discussion

4.1 Experimental Setup

To evaluate the performance of the proposed Taylor algorithm using SLFN and ELM, we provide a simulation implementation of this algorithm. Moreover, the simulation



Fig. 2 Distribution of BSs and MSs.

comparisons are also implemented between the proposed method and other traditional algorithms in different service radius, channel environments, and the number of BSs. Those algorithms compared in this simulation include Chan algorithm, LS algorithm, Taylor series expansion algorithm, and BP based Taylor algorithm (namely, Taylor-BP). Here, instead of using SLFN with ELM in our proposed algorithm Taylor-ELM, Taylor algorithm is implemented based on traditional BP NN in the above algorithm Taylor-BP.

In this simulation, a standard distribution of seven cell BSs of cellular structure with regular hexagon is used, and the service base station BS_1 is located in the center of the community. These seven BSs are scattered on the points of (0, 0), $(-3R/2, \sqrt{3}R/2)$, $(-3R/2, -\sqrt{3}R/2)$, $(0, -\sqrt{3}R)$, $(3R/2, -\sqrt{3}R/2)$, $(3R/2, \sqrt{3}R/2)$, $(0, \sqrt{3}R)$, where *R* is the service radius. Figure 2 shows the distribution of these BSs, and MSs are located in the shadow zone.

We randomly generate 2000 MSs as the target locations. Then we use the TDOA measurement error model mentioned in Sect. 2 to simulate the TDOA measurements under NLOS environment. We divide these analog TDOA measurements into two parts, half are used for NN training in algorithm Taylor-ELM and Taylor-BP, the other half are used for performance evaluation. We assume that the radius of the community is 1000 m, and it will change while comparing the performance of these five algorithms in different community radius. The systematic measurement error η_{i1} is a zero-mean Gaussian distribution with standard deviation $\sigma_{\eta_{i1}} = 30$ m.

4.2 Simulation Results

The simulation results are shown in Fig. 3-7. Figure 3 shows the positioning accuracy of these algorithms under different service radius in urban environment. It is clear that as the community radius increases, the root mean square error (RMSE) of these five algorithms increases. With the increase of cell radius, the distance between MS and BSs is growing which leads to the increase of NLOS errors. In



Fig. 3 The comparison of RMSE in different service radius.



Fig. 4 The comparison of RMSE under different channel environments.

these five algorithms, the performance of Chan algorithm is worst, and the LS and Taylor algorithm are better than it. These three algorithms just take systematic measurement error into consideration, so their performances under NLOS environment are very poor. NN can correct the NLOS error of TDOA measurement, and SLFN using ELM has a higher generalization capability than BP NN. In so doing, the performance of algorithm Taylor-ELM is superior to that of Taylor-BP.

In Fig. 4 and Fig. 5, with the deterioration of the channel environment and the increase of NLOS errors, the estimation error of location is gradually increasing and the proportion of error within 125 m (i.e., the probability that positioning error is less than 125 m) is gradually decreasing. Here the channel environment is described by $T_1 (\mu s)$ defined in Table 1. The performances of Taylor-BP and Taylor-ELM are both superior to Taylor, Chan, and LS algorithms. However the location precision of Chan and LS algorithms has a large decline with the degeneration of the environment. Compared with Taylor-BP, Taylor-ELM is more effective,



Fig. 5 The comparison of proportion of error within 125 m under different environments.



Fig. 6 The comparison of RMSE in different number of BSs.

which is due to that the solution of the ELM can not only have the minimum training error, but also have the smallest norm of weights, which make ELM tend to have a better generalization performance than traditional gradient-based learning algorithms like BP. Taylor-ELM can achieve satisfying positioning accuracy by effectively suppressing the influence caused by NLOS errors.

Figure 6 shows the RMSE of those five algorithms (i.e., Taylor-ELM, Taylor-BP, Taylor, Chan, LS algorithms) in NLOS environment ($T_1 = 0.4$) and the Taylor algorithm in LOS environment under different number of BSs. It is clear that in LOS environment, Taylor algorithm (Taylor-LOS) results an accurate position estimate, but in NLOS environment, its performance degrades greatly. After the correction of the NLOS error through the NN, the accuracy of the position estimate is improved, i.e, the Taylor-ELM and Taylor-BP algorithms can suppress the effect of NLOS error on position estimate. From the figure, we can also know that as the number of BSs increases, the positioning accuracies of these five algorithms are considerably improved. Taylor-



Fig. 7 The comparison of time with different samples.

ELM and Taylor-BP are not sensitive to the number of BSs, and the Taylor-ELM is slightly better than Taylor-BP.

From Fig. 3 to Fig. 6, it shows that the positioning accuracy of Taylor-ELM is higher than Taylor-BP and other algorithms in the same conditions. Figure 7 shows that the training time of Taylor-ELM is much shorter than that of Taylor-BP with the increase of size of training set. The reason is that the gradient-based learning is very timeconsuming, while the learning time of ELM is just spent on solving a linear equation, which leads that the learning speed of ELM is extremely fast. Therefore, it is obvious that algorithm Taylor-ELM can enhance the accuracy, and it also reduces energy consumption that is a key factor for the practical applications of WSN.

5. Conclusion

This paper proposes a novel scheme to enhance the positioning accuracy of mobile station under NLOS environment. The proposed scheme is designed based on a SLFN architecture optimized by ELM learning algorithm. And this scheme uses Taylor algorithm to locate the positions of MSs. The key idea of our approach is to reduce the NLOS error of the TDOA measurement with the help of the high generalization performance, and fast adaptability and nonlinear approximation capabilities of ELM. ELM does not require any parameter tuning, and the initial weights do not affect the prediction performance. The simulation shows that the proposed algorithm can reduce the influence of NLOS error on positioning accuracy to some extent, and its performance is better than that of Taylor-BP, Taylor, Chan, and LS positioning algorithms. Especially, the learning speed of ELM is extremely faster than classic gradient-based learning algorithms like BP. Therefor, combining ELM based SLFN with Taylor algorithm can not only greatly enhance the accuracy of positioning, but also increase the positioning speed, which is a key factor in practice for WSN.

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References

- J.W. Branch, C. Giannella, B. Szymanski, R. Wolff, and H. Kargupta, "In-network outlier detection in wireless sensor networks," Knowl. Inf. Syst., vol.34, no.1, pp.23–54, 2013.
- [2] M.J. Chae M J, H.S. Yoo, J.Y. Kim, and M.Y. Cho, "Development of a wireless sensor network system for suspension bridge health monitoring," Autom. Constr., vol.21, pp.237–252, 2012.
- [3] Y.L. Lai and J. Cheng J, "A 2.45-GHz RFID wireless-sensornetwork location tracking system," Proc. Int. Symp. Consum. Electron., pp.133–134, Hsinchu, Taiwan, 2013.
- [4] Z. Su, F. Shang, and R. Wang, "A wireless sensor network location algorithm based on simulated annealing," Proc. Int. Conf. Biomed. Eng. Informatics, pp.1–5, Tianjin, China, 2009.
- [5] B.P. Qu, G. Shao, and Z.R. Jing, "An improved TDOA location algorithm in LOS environment," Proc. Int. Conf. Intelligent Hum.-Mach. Syst. Cybern., vol.1, pp.70–73, Nanchang, China, 2012.
- [6] C.S. Chen, Y.C. Lin, W.H. Liu, and H.N. Shou, "Improved Taylorseries expansion for MS location estimation," Appl. Mech. Mater., vol.52–54, pp.1777–1782, 2011.
- [7] T.C. Yang, L. Jin, and J. Cheng, "An improvement CHAN algorithm based on TOA position," Acta Electr. Sin., vol.37, no.4, pp.819–822, 2009.
- [8] K. Yang, J. An, X. Bu, and G. Sun, "Constrained total least-squares location algorithm using time-difference-of-arrival measurements," IEEE Trans. Veh. Technol., vol.59, no.3, pp.1558–1562, 2010.
- [9] M. Laaraiedh, S. Avrillon, and B. Uguen, "Overcoming singularities in TDoA based location estimation using total least square," Proc. Int. Conf. Signals, Circuits Syst., Medenine, pp.1–4, Tunisia, 2009.
- [10] L.F. Peng, Q.Z. Huang, and Y.S. Lin, "A cooperative localization method based on conjugate gradient and Taylor series expansion algorithms," Proc. Int. Conf. Comput. Sci. Netw. Technol., vol.2, pp.1108–1112, Harbin, China, 2011.
- [11] Y. Mao and K. Zhou, "A location and tracking algorithm based on BP neural network with NLOS propagation," Proc. Int. Conf. Cyber-Enabled Distrib. Comput. Knowl. Discov., pp.396–399, Zhangijajie, China, 2009.
- [12] S. Zhu, J. Cai, M. Du, and P. Chen, "Application of BP neural network in fast location of fault dictionary," Proc. Int. Conf. Electron., Commun. Control, pp.1333–1336, Ningbo, China, 2011.
- [13] F. Liu, "An improved RBF network for predicting location in mobile network," Proc. Int. Conf. Nat. Comput., vol.3, pp.345–348, Tianjian, China, 2009.
- [14] Y. Lu, N. Sundararajan, and P. Saratchandran, "Performance evaluation of a sequential minimal radial basis function (RBF) neural network learning algorithm," IEEE Trans. Neural Netw., vol.9, no.2, pp.308–318, 1998.
- [15] G.B. Huang, Q.Y. Zhu, and C.K. Siew, "Extreme learning machine: theory and applications," Neurocomputing, vol.70, no.1–3, pp.489– 501, 2006.
- [16] C. Kang, H. Lee, and C. Oh, "NLOS Signal detection algorithm for TDOA method in wireless sensor network," Proc. Int. Conf. Adv. Commun. Technol., Phoenix Park, Korea, vol.1, pp.901–904, 2009.
- [17] L. Cong and W. Zhuang, "Non-line-of-sight error mitigation in

TDOA mobile location," Proc. IEEE Global Telecommun. Conf., vol.1, pp.680–684, San Antonio, United States, 2001.

- [18] H. Jiang, J. Xu, and Z. Li, "NLOS Mitigation Method for TDOA Measurement," Proc. Int. Conf. Intelligent Inf. Hiding Multimedia Signal Process., pp.196–199, Darmstadt, Germany, 2010.
- [19] L. Ghouti, T.R. Sheltami, and K.S. Alutaibi, "Mobility prediction in mobile ad hoc networks using extreme learning machines," Procedia Comput. Sci., vol.19, pp.305–312, 2013.
- [20] H.J. Rong and G.S. Zhao, "Direct adaptive neural control of nonlinear systems with extreme learning machine," Neural Comput. & Applic., vol.22, no.3–4, pp.577–586, 2013.
- [21] G.B. Huang, H. Zhou, X. Ding, and R. Zhang, "Extreme learning machine for regression and multiclass classification," IEEE Trans. Syst. Man Cybern. B, Cybern., vol.42, no.2, pp.513–529, 2012.
- [22] G.B. Huang, Q.Y. Zhu, and C.K. Siew, "Extreme learning machine: a new learning scheme of feedforward neural networks," Proc. IEEE Int. Conf. Neural. Netw., vol.2, pp.985–990, Budapest, Hungary, 2004.
- [23] Y. Hu, D. Ma, and T. Tian, "Node self-positioning in wireless sensor networks using graded estimation and Taylor-series algorithm," Proc. World Congr. Intelligent Control Autom., pp.6711– 6714, Chongqing, China, 2008.
- [24] M. Soltanian, A.M. Pezeshk, A. Mahdavi, and M. Dallali, "A new iterative position finding algorithm based on Taylor series expansion," Proc. Iran. Conf. Electr. Eng., pp.1–4, Tehran, Iran, 2011.
- [25] J.Y. Xiong, W. Wang, and Z.L. Zhu, "A new TDOA location technique based on Taylor series expansion in cellular networks," PD-CAT Proc. Parallel Distrib. Comput. Appl. Technol., pp.378–381, Chengdu, China, 2003.



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