http://ansinet.com/itj

ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 12 (23): 7143-7147, 2013
ISSN 1812-5638 / DOI: 10.3923/itj.2013.7143.7147

A TDOA localization Algorithm Based on Elman Neural Network for Cellular networks

[1]Weiguo Guan, [2]Baochun Lu, [2]Baoguo Li and [2]Pijie Jiang
[1]College of Electronic and Information Engineering,
[2]College of Electrical Engineering, Liaoning University of Technology, Jinzhou, 121001, Liaoning, China

Abstract: The Non-Line-of-Sight (NLOS) error caused by positioning signal reflection and refraction has always been obstacles to improve TDOA positioning performance in mobile localization. Although many researches have invented to mitigate the NLOS influence and some of them has improved the positioning accuracy effectively. However, they were impeded to provide the accurate estimate of NLOS. In this study, TDOA ranging error model is analyzed and a novel localization algorithm based on Elman neural network is proposed to estimate and mitigate NLOS error in TDOA positioning, The estimation and correction for NLOS errors is achieved by Elman neural network without NLOS prior information firstly, then the TDOA data are reconstructed to mitigate the NLOS errors, finally, position solution is estimated by the two-step Weighted Least Squares. The simulation results show that the proposed algorithm has better localization performance in localization precision than the basic positioning algorithm and existing improved even in serious NLOS environment.

Key words: NLOS, localization, Elman neural network, TDOA reconstruction

INTRODUCTION

Location Based Service (LBS) has become one of the important value-added services in 3G networks. Among numerous localization technologies, Time Difference of Arrival (TDOA), as an ideal one with the unnecessarily strict time synchronization between Mobile Station (MS) and Base Station (BS) and less modification in equipments, can be applied to all the mobile communication systems. Chan algorithm, a classic localization algorithm based on TDOA, shows high precision under circumstances of Line-of-Sight (LOS) while algorithm performance will be greatly decreased by the effects of NLOS (Liu *et al*., 2012). So, NLOS error is the major factor influencing location precision. How to mitigate NLOS in the positioning becomes the focus of localization study. Many researches have proposed positioning algorithms which can be divided into two categories: The first one needs to reconstruct the original measured value with priori information of NLOS errors and then estimates location using the data (Boccadoro *et al*., 2012). However, it is difficult to obtain the priori statistical information of NLOS in effect. The second one needs no priori knowledge location algorithm of NLOS error (Lisien *et al*., 2003; Yu and Guo, 2008). As described in (Sun and Hu, 2009), localization algorithm based on minimum entropy estimation is raised which is no need to know the distribution of NLOS error but with a high computing complexity.

Elman neural network, a kind of dynamic recursive neural network, possesses memory characteristics on historical data, thus having a strong ability to adapt to the time-varying conditions. In this study, TDOA location algorithm based on Elman neural network is proposed to estimate NLOS errors in the TDOA ranging data and reconstruct the TDOA data to mitigate NLOS errors. Weighted least squares (WLS) algorithm is applied to location estimation using the reconstructed TDOA data, so the localization accuracy in NLOS environment is improved.

TDOA MEASUREMENT ERROR MODEL

TDOA measurement errors include the system measurement errors and NLOS errors. Suppose TDOA measurement values between MS to BS_i and MS to BS_1 can be expressed as below:

$$\tau_{i,1} = \tau^0_{i,1} + n_{i,1} + \tau_{nlosi,1}, i = 2,3,\ldots\ldots,M \tag{1}$$

where, $\tau^0_{i,1}$ represents the TDOA measurements in LOS environment, $n_{i,1}$ is measurement error following Gaussian distribution with zero mean and $\sigma^2_{ni,1}$ variance, $\tau_{nlosi,1}$ is the NLOS error.

In practical channel, NLOS interference will lead to TDOA measurement error. More errors are made by NLOS in an urban environment (Liu *et al*., 2012). NLOS errors

Corresponding Author: Weiguo Guan, College of Electronic and Information Engineering, Liaoning University of Technology, Jinzhou, Liaoning, China

can be described with power-delay distribution by COST 259 model, it is considered to be subject to typical index distribution in general case, the probability density is followed by Eq. 2:

$$P(\tau) = \begin{cases} \frac{1}{\tau_{rms}} \exp(-\frac{\tau}{\tau_{rms}}) & \tau > 0 \\ 0 & \tau \leq 0 \end{cases} \quad (2)$$

where, τ_{rms} denotes delay spread determined by channel environment. In urban environment, NLOS excess delay t is approximately considered as $t \approx \tau_{rms}$, τ_{rms} follows lognormal distribution (Yu and Guo, 2008).

$\tau_{rms} = T_1 d^{\varepsilon} \xi$. Where T_1 denotes the median of τ_{rms} 1 km away. d denotes the distance between BS and MS. ε is exponential component with range in 0.5~1. ξ denotes random variable subjecting to lognormal distribution with 0 mean and 4~6dB standard deviation. The mean and variance of NLOS additional delay can be formulated as Eq. 3 below:

$$\begin{cases} E(t_{i,NLOS}) = T_1 d_i^{\varepsilon} e^{m_z + \frac{\sigma_z^2}{2}} \\ D(t_{i,NLOS}) = (T_1 d_i^{\varepsilon})^2 e^{2m_z + \sigma_z^2} (2e^{\sigma_z^2} - 1) \end{cases} \quad (3)$$

CORRECTION OF TDOA MEASUREMENTS BASED ON ELMAN NEURAL NETWORKS

A modified model of TDOA measurements based on Elman neural network (Cheng *et al*., 2002) is shown in Fig. 1. The six neurons in input layer are the TDOA measurements in NLOS environment.

Set the input sample vector u(k-1) = [$\tau_{2,1}$, $\tau_{3,1}$, $\tau_{4,1}$, $\tau_{5,1}$, $\tau_{6,1}$, $\tau_{4,1}$] and then the output layer consists of six neurons, standing for TDOA values after correction. Elman neural network is composed of input layer, hidden layer, context layer and output layer. The output of hidden layer is self-connected with the input of the hidden layer through the delay and storage of the context layer. The self-connection makes the network be sensitive to history state data, thus increasing the processing ability for dynamic information. In addition, the convergence layer adds a self-feedback connection gain factor α for memorizing output of convergence layer at the previous moment. α solves the disadvantage that Elman neural network can only identify the first-order system, ($0 \leq \alpha \leq 1$). When α, the network is a typical Elman neural nets; when $\alpha \neq 0$, the network is a modified Elman neural networks (Gao *et al.*, 2012). w^{11}, w^{12} and w^{13}, respectively, the connection weight matrix between convergence layer and hidden layer, input layer and hidden layer, hidden layer and output layer. X(k) and $x_c(k)$ are the output of hidden layer and convergence layer. The transfer function f(.) of hidden layer neurons often adopts the sigmoid function; linear function is adopted to be the transfer function g(.) of output neurons.

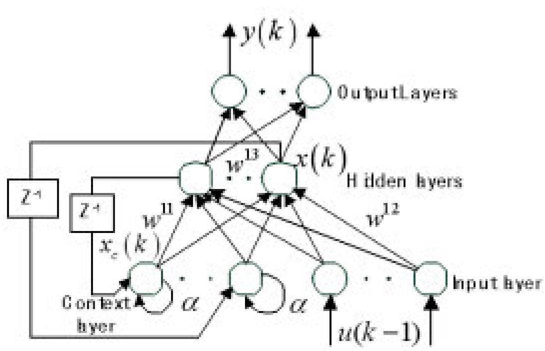

Fig. 1: Elman neural network structure

ELMAN NEURAL NETWORK BASED TDOA LOCALIZATION ALGORITHM

TDOA data correction based on the Elman network: The processing steps of TDOA positioning parameters based on Elman neural network are as follows. Assuming that there are K sets of measured TDOA parameters under NLOS environment which is selected as the input samples, TDOA values without measurement errors and NLOS errors are defined as the target vector to train the Elman neural network, then the training process can be summarized as follows:

Step 1: Initialize the connection weights between layers as a random number between (-1, 1)

Step 2: Input TDOA measuring samples, for each sample, according to the step (4)~(6) calculate the output of hidden layer, context layer and output layer:

$$x(k) = f(w^{11}x_c(k)+w^{12}u(k-1)) \quad (4)$$

$$x_c(k) = \alpha x_c(k-1)+x(k-1) \quad (5)$$

$$y(k) = g(w^{13}x(k)) \quad (6)$$

Step 3: Error of the TDOA samples is calculated according to the Eq. 7, where $y_d(k)$ is the expectation output:

$$E(k) = \frac{1}{2}(y(k)-y_d(k))^T(y(k)-y_d(k)) \quad (7)$$

Step 4: In order to improve the learning rate and enhance the reliability of the algorithm, we adopt the BP learning algorithm with a linear momentum item to update the connection weights between layers (Liu *et al*., 2004), the update equation is as follows:

$$w_{ij}^{13}(k+1) = w_{ij}^{13}(k) + \eta_3\delta_i^0 x_j(k) + \gamma_3\left(w_{ij}^{13}(k) - w_{ij}^{13}(k-1)\right) \quad (8)$$

$$w_{jq}^{12}(k+1) = w_{jq}^{12}(k) + \eta_2\delta_i^h u_q(k-1) + \gamma_2\left(w_{jq}^{12}(k) - w_{jq}^{12}(k-1)\right) \quad (9)$$

$$w_{jl}^{11}(k+1) = w_{jl}^{11}(k) + \eta_1\sum_{i=1}^{m}\left(\delta_i^0 w_{ij}^{13}\right)\frac{\partial x_j(k)}{\partial w_{jl}^{11}} + \gamma_1\left(w_{jl}^{11}(k) - w_{jl}^{11}(k-1)\right) \quad (10)$$

where, η_1, η_2 and η_3 are the learning rates of w^{11}, w^{12} and w^{13}, respectively, γ_1, γ_2 and γ_3 are the momentum coefficients of w^{11}, w^{12} and w^{13}. Their Values are between (0, 1); here, $\delta^0_i = y_{d,i}(k)-y_i(k)$:

$$\delta_j^h = \sum_{i=1}^{m}\left(\delta_j^h w_{ij}^{13}\right)f_j'(\cdot),\ \frac{\partial x_j(k)}{\partial w_{jl}^{11}} = f_j'(\cdot)x_l(k-1) + \alpha\frac{\partial x_j(k-1)}{\partial w_{jl}^{11}}$$

Step 5: Calculate global error according to Eq. 11 and judge whether the global error is less than the stipulated accuracy, If it is, then the network is convergent and the weight should be saved; otherwise, step 6 should be executed:

$$E = \sum_{k=1}^{K} E(k) \quad (11)$$

Step 6: Determine whether reach the maximum number of iterations, if so, then end the iteration and save the weights; otherwise, return to step 2

K set of TDOA measurements data under NLOS environment are input into well-trained Elman network and then TDOA data corrections are obtained. Using the reconstructed TDOA data, WLS localization algorithm is adopted to calculate the location estimates.

Location resolving: Assuming that MS coordinate $z_p = [x, y]$ and BS_i coordinates is (x_i, y_i), i = 1, 2,…M. BS_1 is the serving BS, $\tau^0_{i,1}$ is the time difference between MS to BS_i and MS to BS_1 which is corrected by Elman neural network. The distance difference can be expressed by $R_{i1} = c\tau^0_{i,1}$, MS location can be estimated by solving the following equations:

$$2x_{i1}x + 2y_{i1}y + 2R_{i1}R_1 = K_i + K_1 - R_{i1}^2 \quad (12)$$

where, $K_i = x^2_i+y^2_i$, $K_1 = x^2_1+y^2_1$, $x_{i1} = x_i-x_1$, $y_{i1} = y_i-y1$, c denotes the speed of electromagnetic wave. Firstly, WLS algorithm is used to get the initial solution. Assuming $z_a = [z_p^T, R_1]^T$ is an unknown vector, so TDOA error vector for noises can be expressed as Eq. 13:

$$\psi = h - G_a z_a^0 \quad (13)$$

Where:

$$h = \frac{1}{2}\begin{bmatrix} R_{21}^2 - K_2 + K_1 \\ R_{31}^2 - K_3 + K_1 \\ \vdots \\ R_{M1}^2 - K_M + K_1 \end{bmatrix},\ G_a = -\begin{bmatrix} x_{21} & y_{21} & R_{21} \\ x_{31} & y_{31} & R_{31} \\ \vdots & \vdots & \vdots \\ x_{M1} & y_{M1} & R_{M1} \end{bmatrix},$$

$$Z_a^0 = [x, y, R_1^0]^T$$

When MS is far away from each BS, R_i (the measured distance between MS and BS_i) is closed to R^0_i (the real distance between MS and BS_i). Assume that Gaussian noise vector is $n = [n_{2,1}, n_{3,1},\ldots, n_{M,1}]^T$ and its covariance matrix is $Q = E(nn^T) = \mathrm{diag}\{\sigma_{21}^2, \sigma_{31}^2, \cdots, \sigma_{M1}^2\}$, the position z_a can be estimated by using the condition of $B = R^0_i I$ as below:

$$z_a \approx \left(G_a^T Q G_a\right)^{-1} G_a^T Q^{-1} h \quad (14)$$

If MS is near the BS, an initial solution should be calculated by Eq. 14 to obtain matrix B firstly, then position can be estimated according to Eq. 15 with substitution for matrix B:

$$z_a \approx (G_a^T \Psi^{-1} G_a)^{-1} G_a^T \Psi^{-1} h \quad (15)$$

where, $\Psi = E(\psi\psi^{-1}) = c^2BQB$, Q is covariance matrix of TDOA, $B = \mathrm{diag}(R_2, R_3,\ldots, R_M)$.

Actually, x, y and R_1 are related, so the WLS is applied again. The first estimate coordinates are put to use for the second WLS estimating, then the improved location estimate can be obtained:

$$\psi' = h' - G'z'_a \quad (16)$$

Where:

$$h' = \begin{bmatrix} (z_{a,1} - x_1)^2 \\ (z_{a,2} - y_1)^2 \\ z_{a,3}^2 \end{bmatrix},\ G' = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 1 & 1 \end{bmatrix},\ z_a' = \begin{bmatrix} (x - x_1)^2 \\ (y - y_1)^2 \end{bmatrix},$$

$$\Psi' = E(\psi'\psi'^T) = 4B'\mathrm{cov}(z_a)B',\ B' = \mathrm{diag}\{x - X_1, y - Y_1, R_1\}$$

ψ and ψ' obey Gaussian distribution, so the ML estimation of z'_a can be expressed as follows:

$$z'_a = (G_a'^T \Psi'^{-1} G_a')^{-1} G_a'^T \Psi'^{-1} h' \quad (17)$$

The final result of MS location estimation is made as below:

$$z_p = \pm\sqrt{z_a'} + \begin{bmatrix} X_1 \\ Y_1 \end{bmatrix} \quad (18)$$

One correct root of z_p in Eq. 18 can be selected as final MS location by severing BS information such as Cell-ID. Thus, the final MS location can be determined directly.

SIMULATION AND ANALYSES

Simulation conditions: To validate performance of proposed algorithm, Positioning simulations by Matlab R2008a are carried on in a cellular network with seven cells. The BSs participating in TDOA measurements includes serving station BS1 and other six adjacent BSs: BS_2~BS_7 with cell radius R = 1000 m. MS is uniformly distributed in the area of serving cell. TDOA measurement errors obey independent Gaussian distributions with standard deviation $\sigma_{ni,1}$ = 0.1 us. Meanwhile; there is NLOS environment between BS and MS.

Simulations and analysis: (1) Assuming that NLOS errors obey the index distribution, we made a comparison of Root Mean Square Error (RMSE) between the proposed algorithm, Taylor algorithm, Chan algorithm and SI algorithm in different NLOS noise environments with σ_{NLOS} = (100, 150, 200, 250, 300 and 350 m). As shown in Fig. 2, with the increasing of NLOS error, the errors of Chan algorithm, Taylor algorithm and SI algorithm increase gradually. Because of correction of TDOA parameter by Elman network, the positioning error of the proposed algorithm is much smaller than the other three algorithms (with 110 m accuracy when NLOS noise STD = 200 and 150 m accuracy when NLOS noise STD = 300 m). It shows that the algorithm has stronger stability and better positioning precision than other three algorithms. It also shows that the NLOS correction of Elman neural network effectively restrains the growth of positioning error and improves the localization precision. The algorithm has the resistance ability against NLOS which is not dependent on the priori information of errors, thus it has higher practicality.

Figure 3 shows the positioning cumulative probability distribution curve of the proposed algorithm in Bad Urban, Urban, Suburban and Rural environments. NLOS errors follow logarithmic normal distribution within 900 m. The simulation results show that NLOS estimation

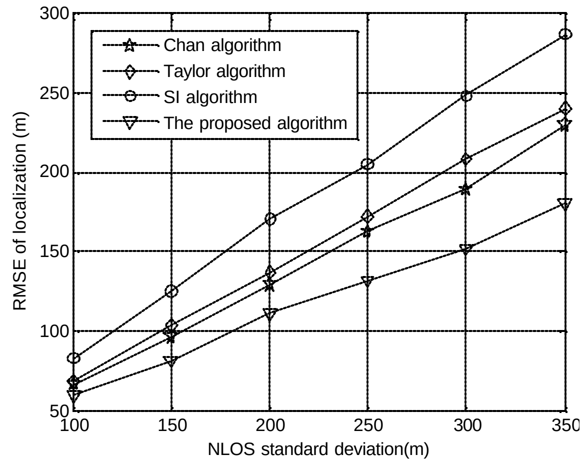

Fig. 2: Localization accuracy comparison

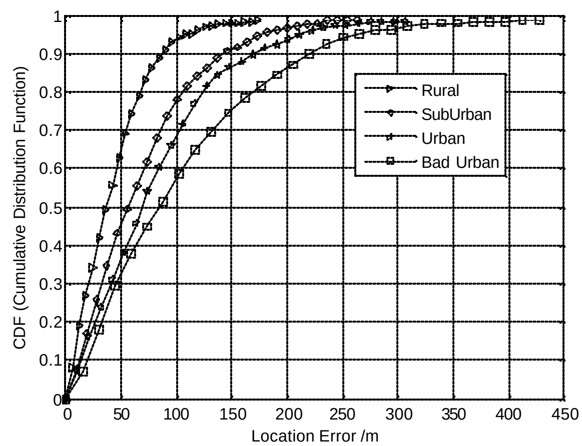

Fig. 3: CDF in various noise conditions

using Elman neural network and TDOA reconstructing in this algorithm have good positioning performance although the NLOS is serious. The algorithm can reach the location accuracy of 96 m in 67% probability under urban environment and the localization accuracy is superior to 170 m in 95% probability when the NLOS error is within 900 m. The precision still meets requirements of the E-911 localization for mobile network which means the proposed localization algorithm can mitigate NLOS error effectively.

CONCLUSION

A TDOA localization algorithm based on Elman neural network is put forward in this study. The algorithm utilizes the nonlinear mapping ability and dynamic sensitivity of Elman neural network, modifies the TDOA measurements under NLOS environment and reduces the influence of NLOS on positioning precision. The simulation results show that the algorithm, with higher location precision and better positioning performance than that of Chan algorithm and Taylor algorithm, has a strong ability to resist the NLOS error. Because the algorithm does not depend on a priori information of NLOS error, it can be widely used in various positioning environments.

ACKNOWLEDGMENTS

This research is supported by Dr. Start Foundation of Liaoning Provincial Science and Technology Department (20131045) and Education Committee Foundation of Liaoning (L2012218).

REFERENCES

Boccadoro, M., G. de Angelis and P. Valigi, 2012. TDOA positioning in NLOS scenarios by particle filtering. Wireless Networks, 18: 579-589.

Cheng, Y.C., W.M. Qi and W.Y. Cai, 2002. Dynamic properties of Elman and modified Elman neural network. Proceedings of the International Conference on Machine Learning and Cybernetics, Volume 2, November 2002, Beijing, China, pp: 637-640.

Gao, X., D. You and S. Katayama, 2012. Seam tracking monitoring based on adaptive kalman filter embedded elman neural network during high-power fiber laser welding. IEEE Trans. Ind. Electronics, 59: 4315-4325.

Lisien, B., D. Morales, D. Silver and G. Kantor, 2003. Hierarchical simultaneous localization and mapping. Proceedings of the International Conference on Intelligent Robots and Systems, Volume 1, October 27-31, 2003, Las Vegas, US., pp: 448-453.

Liu, N., H. Shi, J. Wang and S. Guo, 2012. Research of Mobile Location Estimation with Reducing NLOS Errors. In: Future Control and Automation: Proceedings of the 2nd International Conference on Future Control and Automation, Deng, W. (Ed.). Springer, New York, pp: 471-477.

Liu, Z., M. Liu and F. Qian, 2004. The application of one improved niche genetic algorithm for Elman recurrent neural networks. Proceedings of the 5th World Congress on Intelligent Control and Automation, June 15-19, 2004, Hangzhou, China, pp: 1978-1981.

Sun, G. and B. Hu, 2009. A minimum entropy estimation based mobile positioning algorithm. IEEE Trans. Wireless Commun., 8: 24-27.

Yu, K. and Y.J. Guo, 2008. Improved positioning algorithms for non-line-of-sight environments. IEEE Trans. Vehicular Technol., 57: 2342-2353.