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A Improved Wireless Location Algorithm in Nlos Environment

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Abstract: In order to solve the problem of poor performance of Chan location algorithm based on TDOA parameters in NLOS communication environment, an improved wireless location algorithm is proposed. The fast study and non-linear approach capacity of Radial Basis Function (RBF) neural network is made use of to amend the NLOS error of TDOA measurements and using Chan location algorithm estimates the position. The simulation results show that the algorithm restrained the error of NLOS effectively and improved the positioning accuracy of NLOS propagation environment. Its performance is better than the Chan algorithm and Taylor algorithm and the algorithm has great practical value.

Key words: Wireless location, none line of sight(NLOS); chan algorithm; radial basis function(RBF) neural network; time fifference of arrival (TDOA)

INTRODUCTION

With the era of internet of things, wireless location technology has become an important research topic in recent years. Wireless location technology is widely used in public or commercial services, wireless communications, intelligent transportation systems and wireless sensor networks, etc (Zhang *et al.*, 2013; Zhou, 2013; Tang *et al.*, 2012). There is Time of Arrival (AOA) (Cheng *et al.*, 2004), Time Difference of Arrival (TDOA) (Mao *et al.*, 2007), Angle of Arrival (AOA) (Niculescu and Nath, 2003) and Received Signal Strength (RSS) (Salem, 2011) location technology according to the type of the measured values. Chan algorithm (Chan and Ho, 1994) based on TDOA parameter introduces an intermediate variable parameters to convert the nonlinear equations into linear equations and uses quadratic estimation method to achieve location it is a high precision and simple location algorithm. In the case of the TDOA measurements error is smaller, the Chan algorithm has optimal estimation performance butwith the increase of TDOA measurements error, the performance is rapidly declining, the Non-Line-Of-Sight (NLOS) propagation is an important factor of TDOA error. Due to widespread NLOS propagation environment in the urban, TDOA measurements error is bigger, so rely on Chan algorithm of TDOA parameter in the NLOS channels environment positioning performance is poorer, positioning accuracy is lower. In order to solve this problem, researchers have proposed TDOA cooperative location algorithm based on Than and Taylor (Chen *et al.*, 2011), Chan algorithm is used to calculate the TDOA measurements as initial value of the Taylor series expansion algorithm and gets the estimated value of the location after multiple iterations. But this method does not consider the error of TDOA value due to the poor channel environment, therefore it has great influence on the location results. Some researchers have proposed a cooperative location method based on K-nearest neighbor and Chan algorithms (Liu and Lu, 2012), it has stable position performance and small amount of calculation butthe accuracy is poor.

To solve these problems, an improved algorithm is proposed. Analyzing the error of TDOA value that was measured in the environment of NLOS channels first, the fast study and no-linear approach capacity of the RBF neural net work is made use of to amend the NLOS error of TDOA measurements, then the Chan algorithm is used to locate the Mobile Station (MS), the performance of the algorithm are analyzed and simulated finally. The Radial Basis Function (RBF) neural network is a typical forward neural network, since it has nonlinear continuous function and the training speed and other characteristics it widely used in function fitting, pattern recognition, artificial intelligence, etc (Jiang *et al.*, 2013; Wang *et al.*, 2010).

TDOA MEASUREMENTS ERROR ANALYSIS

In the NLOS environment, considering the additional delay error because of the NLOS, Assume the TOA measurements between the MS and the i beacon station (BSi) is:

$$R_i = R_i' + s_i + \tau_i, i = 1, 2, ..., M \quad (1)$$

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where, s_i is the system error with the mean value is 0 and the variance is σ_{si}^2 and obeys gaussian distribution. τ_i is NLOS error of TOA measurements. It is random number with the mean value is positive number (denoted by μ^i) and the variance is σ_i^2 Each s_i and τ_i are independent, M represents the number of BS. R'_i represents the TOA measurements in the LOS environment as follow:

$$R_i^{'} = \sqrt{(x-x_i)^2+(y-y_i)^2}, i=1,2,...,M \tag{2}$$

where, the (x,y) is the coordinate of MS and (xi,yi)is the coordinate of BSi. So we obtain the TDOA measurements in NLOS environment as follow:

$$\begin{aligned} R_{i,1} &= R_i - R_1 = (R_i^{'} - R_1^{'}) + (s_i - s_1) + (\tau_i - \tau_1) \\ &= R_{i,1}^{'} + s_{i,1} + \tau_{i,1} \end{aligned} \tag{3}$$

where, $s_{i,1}$ is the system error in NLOS environment with the mean value is 0 and the variance is σ_{si}^2 and obeys gaussian distribution. $\tau_{i,}$ is NLOS noise of TOA measurement. It is random number with the mean value is $\mu_i+\mu_1$ and the variance is $\sigma_i^2+\sigma_i^2$. Because $\tau_{i,}$ obeys exponential distribution (Bian *et al*., 2013) and the probability density is:

$$f(\tau_{nlos} \mid \tau_{rms}) = \begin{cases} \frac{1}{\tau_{rms}} \exp(\frac{\tau_{nlos}}{\tau_{rms}}), \tau_{nlos} > 0 \\ 0 \qquad\qquad\qquad , \text{else} \end{cases} \tag{4}$$

where, $\tau_{rms} = T_1 d_i^{\varepsilon} \xi$ is RMS delay spread(unit is us), d_i^{ε} is distance between MS and BSi(unit is km), ξ obeys normal distribution with the mean value is 0 and standard deviation is σ_ξ range 4-6dB.T1 is equal to τ_{ms} when d_i^{ε} is 1km.T1 has different value for different channel parameters.T1 was 1.0, 0.4, 0.3, 0.1, respectively in downtown area, generally city, suburb and outer suburban district.

CHAN LOCALIZATION ALGORITHM BASED ON RBF NEURAL NETWORK

Chan algorithm: Assume there are M BS in the two-dimensional space, MS's coordinate is (x,y), the position of BS(xi,yi) is known. So the TDOA measurements between MS and BSi and BS1 is:

$$R_{i,1} = \sqrt{(x_i - x)^2 + (y_i - y)^2} - \sqrt{(x_1 - x)^2 + (y_1 - y)^2} \tag{5}$$

Transform (5) into:

$$2x_{i,1}x + 2y_{i,1}y + 2R_{i,1}R_1 = K_i - K_1 - R_{i,1}^2 \tag{6}$$

where, $x_{i,1} = x_i$-x_1, $y_{i,1} = y_i$-y_1, $K_i = x_i^2 + y_i^2$, $K_1 = x_1^2 + y_1^2$ R1 is TOA measurements between MS and BS1.

When M>3,the error vector of TDOA noise is defined as $\mathbf{\Psi}$:

$$? = h - G_a z_a^0 \qquad i = 2,3,...,M \tag{7}$$

where, $z^0{}_a$ represents the ture value of aircraft:

$$h = \frac{1}{2}\begin{bmatrix} R_{2,1}^2 - & K_2 + & K_1 \\ R_{3,1}^2 - & K_3 + & K_1 \\ & \vdots & \\ R_{M,1}^2 - & K_M + & K_1 \end{bmatrix}$$

$$G_a = -\begin{bmatrix} x_{2,1} & y_{2,1} & R_{2,1} \\ x_{3,1} & y_{3,1} & R_{3,1} \\ & \vdots & \\ x_{M,1} & y_{M,1} & R_{M,1} \end{bmatrix}$$

When TDOA noise is small, the error vector is:

$$\begin{aligned} ? &= 2Bn + n \bullet n \\ B &= \text{diag}\left\{R_1^{\circ}, R_2^{\circ}, ..., R_i^{\circ}, ..., R_M^{\circ}\right\} \end{aligned} \tag{8}$$

where, R_i° is the real distance between MS and BSi.n is TDOA error. So we can receive:

$$? = E(??^T) = c^2 BQB \tag{9}$$

where, $Q = \text{diag}\{\sigma_{21}^2, \sigma_{31}^2, ..., \sigma_{M1}^2\}$ is covariance matrix of TDOA. Assume the various elements of Z_α are independent, so we can receive Z_α by using weighted least square method (WLS):

$$z_a = (G_a^T ?^{-1} G_a)^{-1} G_a^T ?^{-1} h \tag{10}$$

Considering the correlation of R1 and MS in practice, the error vector is$\mathbf{\Psi}$' can be expressed as:

$$?' = h' - G_a' z_a' \tag{11}$$

Where:

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

$$?' = E(?'?'^T) = 4B' \operatorname{cov}(z_a)B', B' = \operatorname{diag}\{x^0 - x_1, y^0 - y_1, R_1^0\}$$

Because of obeying to Gaussian distribution of **Ψ**, **Ψ**, obeys to the Gaussian distribution too. So Maximum Likelihood (ML) estimate of z_α is defined as:

$$\operatorname{cov}(z_a') = (G_a'^T ?' G_a')^{-1}$$

$$z_p = \sqrt{z_a'} + \begin{bmatrix} x_1 \\ y_1 \end{bmatrix} \quad \text{or} \quad z_p = -\sqrt{z_a'} + \begin{bmatrix} x_1 \\ y_1 \end{bmatrix} \tag{12}$$

On account of the covariance matrix of z_α is expressed as:

$$\operatorname{cov}(z_a') = (G_a'^T ?' G_a')^{-1}$$

At last, the final result of MS positioning is that:

$$z_p = \sqrt{z_a'} + \begin{bmatrix} x_1 \\ y_1 \end{bmatrix} \quad \text{or} \quad z_p = -\sqrt{z_a'} + \begin{bmatrix} x_1 \\ y_1 \end{bmatrix} \tag{13}$$

Chan algorithm positioning accuracy is high when the noise obeys Gaussian distribution butit would fall significantly in NLOS environment.

TDOA corrected value based on RBF neural network: Although it can solve nonlinear equations by using the weighted least square, the error is larger in NLOS environment (Mao, 2008). In order to solve this problem, we amend the TDOA measurements by using RBF neural network with the global optimization and no-linear approach capacity. The RBF neural network model is shown in Fig. 1, it is composed of input layer, hidden layer and output layer. To obtaining more accurate TDOA value, we consider six BS and a MS to get six TDOA value as input. The basis functions of hidden layer responses to an input signal, the closer the input signal range of the center of the basis function, the greater output value of hidden layer, so the network structure has a good local approximation characteristics. The basis function of hidden layer obeys Gaussian distribution as follow:

$$R_i(x) = \exp[-\frac{\| x - c_i \|}{2\sigma_i^2}, i = 1, 2, ..., M \tag{14}$$

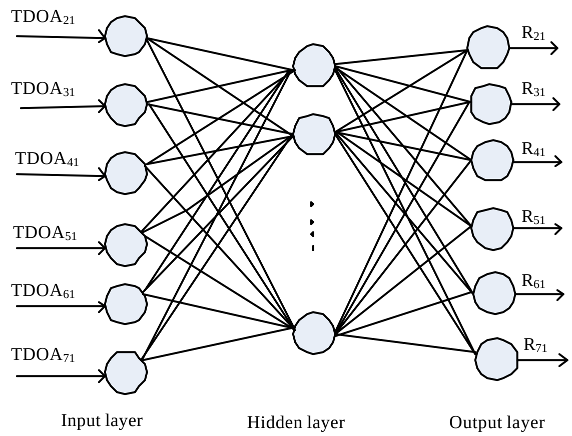

Fig. 1: TDOA value correction model of RBF neural network

where, M represents the number of hidden layer neurons, X = I = [$TDOA_{21}$, $TDOA_{31}$, $TDOA_{41}$, $TDOA_{51}$, $TDOA_{61}$, DOA_{71}] is input vector, Ci is center of the i basis function.§Ò$_i$ is the width of the basis function around the central point. ||X-Ci|| is the norm of vector X-*Ci*. Ri(x) decays to zero rapidly as the ||X-Ci|| increasing. The output layer is composed of six neurons and the output value is 6 TDOA measurements be expressed as P = [y1, y2, y3, y4, y5, y6] = [R_{21}, R_{31}, R_{41}, R_{51}, R_{61}, R_{71}].

There are three parameters to be learn is RBF's center, variance and weight of output unit in RBF network. They are trained by using gradient descent method (Wang and Xue, 2011). Assume the number of unit of hidden is M, training sample is N group, the error function is mean square and the |Ñ1,|Ñ2and|Ñ3 are learning rate. The real output is expressed as:

$$\hat{y}_k(t)$$

expectation output is expressed $y_k(t)$. so the system error can be expressed as:

$$e_k(t) = \hat{y}_k(t) - y_k(t), k = 1, 2, ..., N° \tag{15}$$

Because of:

$$\frac{\partial \bar{E}(t)}{\partial w_i(t)} = \frac{\partial \bar{E}(t)}{\partial y_i(t)} \frac{\partial y_i(t)}{\partial w_i(t)} = \frac{2}{N} e_k \varphi_i (\| x_k - c_i \|)$$

so the weights of output unit can be expressed as:

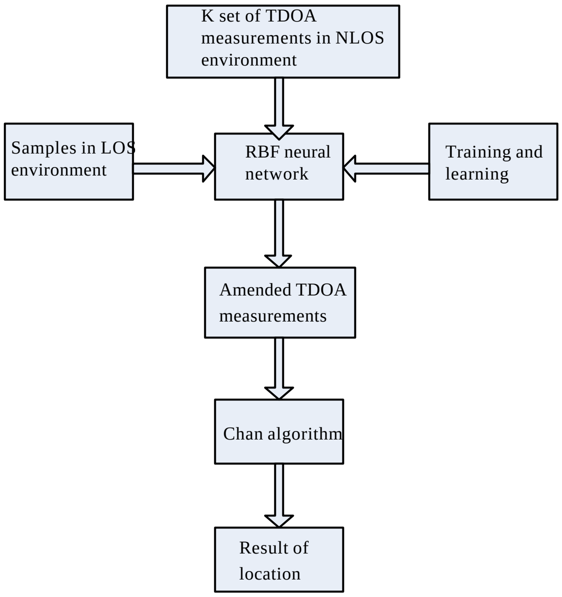

Fig. 2: Flow diagram of the improved Chan algorithm

$$w_i(t+1) = w_i(t) - \rho_1 \frac{\partial \bar{E}(t)}{\partial w_i(t)} \qquad (16)$$

The center of the hidden layer unit is that:

$$c_i(t+1) = c_i(t) - \rho_2 \frac{\partial \bar{E}(t)}{\partial c_i(t)}$$

Where:

$$\frac{\partial \bar{E}(t)}{\partial c_i(t)} = \frac{\partial \bar{E}(t)}{\partial y_k(t)} \frac{\partial y_k(t)}{\partial c_i(t)} = \frac{2}{N} e_k \frac{(x_k - c_k)}{\sigma_i^2} \varphi_i(\| x_k$$

The width of the basis function around central point is that:

$$\sigma_i(n+1) = \sigma_i(n) - \rho_3 \frac{\partial E(n)}{\partial \sigma_i(n)} \qquad (18)$$

Procession of chan algorithm based on BRF neural network: The delaying spread channel model is $\tau_{rms} = T_1 d_i^{\varepsilon} \xi$ in NLOS environment, we can obtain the TDOA measurements error. Considering the NLOS error and system error, the TDOA measurements is amended by using RBF neural network. Because the TDOA value is more close to the ideal conditions of TDOA measurements, so the performance location is better after using Chan algorithm calculates it. The flow diagram of improved Chan algorithm based on RBF neural network is showed in Fig. 2. Specific steps as follow:

Considering NLOS error and system error, we obtain a set of TDOA measurements in the case of multi-base station.

The RBF neural network is trained and its sample vector is TDOA measurement in LOS environment, then establishing RBF neural network for amending NLOS error.

TDOA measurements of (1) are amended by using the neural network of (2).

TDOA measurements of (3) are calculated by using Chan algorithm for getting the location of MS.

SIMULATION

Condition of simulation: In order to verify the effectiveness of the improved Chan algorithm, we simulate to the algorithm in all kinds of conditions. Condition of simulation is as follow:

The simulation tool is Matlab7.11.0. Considering NLOS propagation environment.

The number of involved base stations is 7, the sixth beacon nodes is:

$$BS_1(0,\sqrt{3}R), BS_2(3R/2,\sqrt{3}R/2),$$
$$BS_2(3R/2,-\sqrt{3}R/2), BS_5(-3R/2,-\sqrt{3}R/2),$$
$$BS_6(-3R/2,\sqrt{3}R/2)$$

200 nodes distribute in regular hexagon and the high of regular hexagon is $\sqrt{3}R/2$ and the center coordinate is (0,0).

The channel parameters is 0.4.R is 1km.TDOA measurements error obey Gaussian distribution and mean value is 0 and standard deviation is 0.5us.

Simulation steps and result analysis

Simulation steps: Distributing 200 nodes random and generating 200 analog measurement data.

Establishing and training RBF neural network. The network is trained and the 200 real TDOA values are the sample vector. Fixing the number of neurons in hidden layer first it is 15 here. Observing the imitative effect of the hidden layer when we change it.

The simulated TDOA measurements of (1) by using the trained neural network for performance simulation. Simulated TDOA measurements are amended by using trained RBF network and then using the Chan algorithm calculates the amended TDOA measurements changing the size of R and NLOS channel parameters. we can observe the change between the estimated position and real position of nodes.

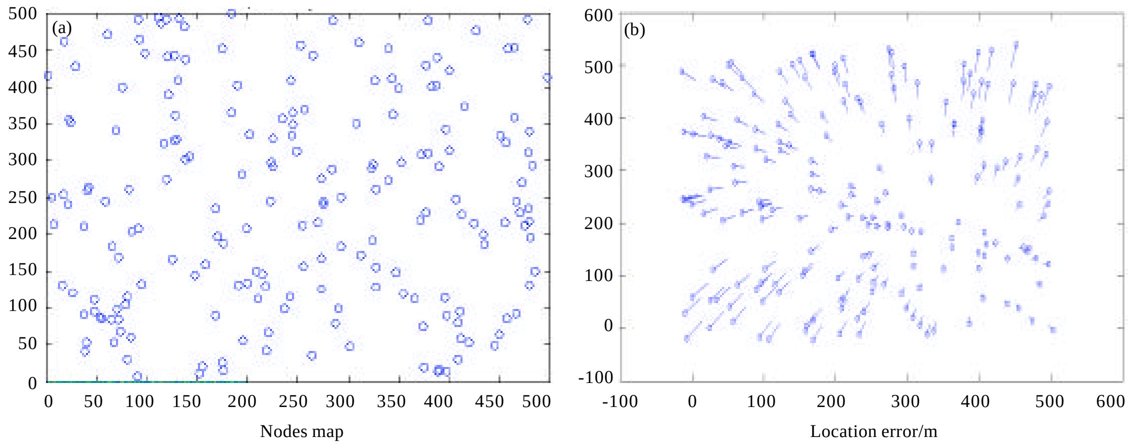

Fig. 3(a-b): Nodes localization of regional of radius of 500 m, (a) Nodes map and (b) Differences of the real position and measurement position

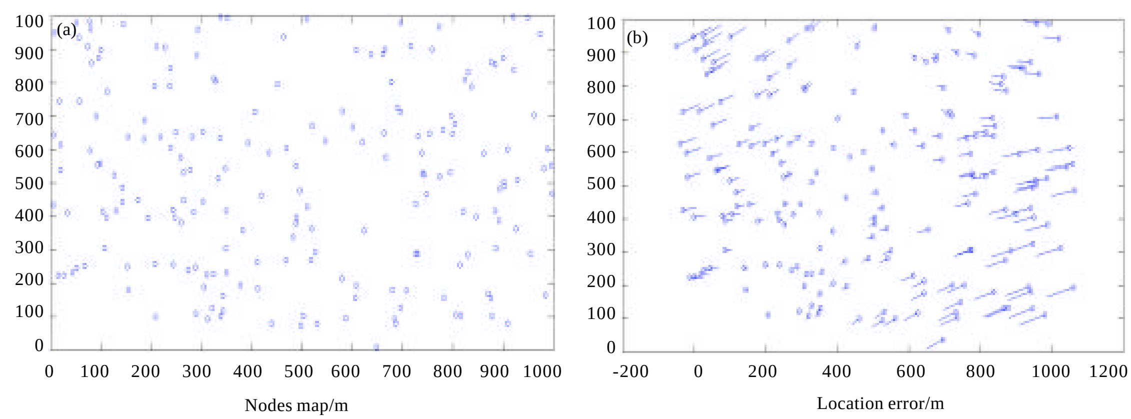

Fig. 4(a-b): Nodes localization of regional of radius of 1km, (a) Nodes map and (b) Differences of the real position and estimated position

Results analysis: The simulation results show that a layer of the network can achieve good positioning results and simple network structure, the training time is short and easy to implement relatively. The hidden layer neurons are 22 be best fit.

Nodes location estimation performance is shown in Fig. 3 when R is 500 m, the Fig. 3a is 200 node distribution random and Fig. 3b is the difference between the estimated position and the real position of the 200 nodes. Where the point of O is estimated position. We can conclude that the error is very small, the mean error is 12.3165 m.The RMSE is 16.955 m when R is 1km and other conditions are same as the Fig. 3 as show in Fig. 4. We can obtain the changing curve of mean error when we change the size of R. Original Chan algorithm and Taylor are used to located nodes in the same conditions as show in Fig. 5. The figure shows three kinds of algorithms positioning error by the increase of R which Chan worst algorithm positioning accuracy, Taylor followed, this paper improved algorithm to locate the highest accuracy.

Due to changes in the distribution of the nodes only affect the measurement error and the NLOS error because of the changing channel parameters is far greater than the system error. The RMSE of three location algorithm are showed in Fig. 6 when we change the channel parameters. We can conclude that the improved Chan algorithm this paper inhibited the growth of RMSE effectively. It has good reliability and stability relative to the other two algorithms.

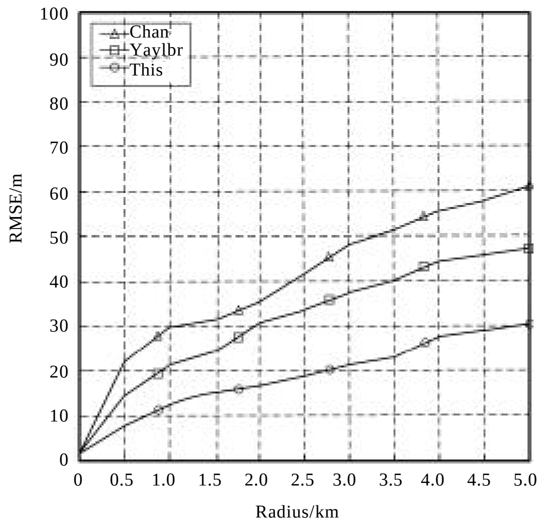

Fig. 5: RMSE OF changing with radius

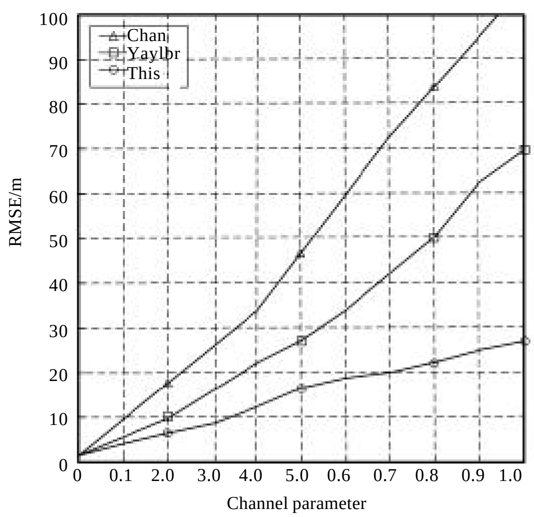

Fig. 6: RMSE of changing channel parameter

CONCLUSION

A improved Chan location algorithm based RBF neural network is proposed. RBF neural network model is established through learning and training and then using the trained neural network model amend TDOA measurements in NLOS environment and the MS location by using Chan algorithm to reduce the influence of NLOS error. Simulation show that the improved algorithm good reliability and stability relative to the other two algorithms. Compared with other classical algorithm under the same conditions, the proposed algorithm is of high speed and high precision and it has broad applicability location environment.

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