UWB localization algorithm based on BP neural network compensation extended Kalman filter

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Abstract. When UWB technology is applied to indoor positioning, there will be a lot of noise interfering with its positioning accuracy. In order to improve the positioning accuracy, the improved extended incremental Kalman filtering algorithm and BP neural network algorithm are proposed to eliminate the positioning errors. In this paper, the extended incremental Kalman filter algorithm is first used to denoise the distance measured by UWB to reduce the errors caused by environment, equipment and other factors, then the classical Chan positioning algorithm is used to get the positioning results of tags, and finally the BP neural network algorithm is used to compensate the positioning results.

1. Introduction
UWB has the advantages of high resolution, anti-multipath effect, strong penetration, simple hardware structure and high frequency spectrum utilization. It has become a good physical layer technology for indoor high-precision positioning application [1]. Among many localization algorithms, TDOA is widely used because of its low requirement of clock synchronization, simple equipment and high positioning accuracy [2]. In the process of UWB positioning technology, there are many factors leading to its positioning accuracy reduction. In addition to the multipath propagation and non-line-of-sight interference, hardware equipment and measuring equipment also produce system errors, which reduce positioning accuracy.

There are many methods to suppress non-line-of-sight error and improve positioning accuracy. The translation invariant denoising method based on the improved wavelet threshold method can effectively suppress the error [3]. The simulation results show that this denoising method can obviously improve the SNR, and its effect is indeed better than the traditional soft and hard threshold denoising methods. But the positioning accuracy still needs to be improved. One of the more common methods is Kalman filtering. The general idea of untrace Kalman filter is to combine Kalman linear filter framework and UT transform to deal with the nonlinear transfer problem of mean and covariance, so as to improve the filtering effect of nonlinear problem [4]. However, UWB positioning coordinates need to be collected several times in the beginning stage to calculate the initial value of the system state and variance. Autoregressive Kalman filter (ARKF) is one of the most effective methods to suppress NLOS, which sets thresholds and adds discrimination and substitution in conventional Kalman filter. However the determination of the threshold is determined by the test effect, practicability is not strong [5]. There is also a collaborative location algorithm based on Chan and Taylor [6]. But the positioning accuracy is not enough. Moreover, in the actual application of UWB positioning technology, it is found that there are measurement system errors caused by the interference of environment and measuring equipment or the difficulty of self-calibration in the environment, which are caused by measurement equations [7]. Therefore, the extended incremental Kalman filter method is adopted in this paper to effectively...
eliminate the non-line-of-sight error and measurement system error. Combined with Chan algorithm to achieve positioning, estimation results are used as the trained BP neural network input for correction, the output of BP neural network is the final positioning results. Simulation results show that the algorithm has good stability and improves the positioning accuracy significantly.

2. Extended Incremental Kalman Filtering Algorithm

In order to reduce the influence of non-line-of-sight error and measurement system error on positioning accuracy, the following ranging model is established.

\[ d_n(t) = D_n(t) + N_n(t) + i_n(t) + f_n(t) \]

(1)

In the above formula, \( d_n(t) \) and \( D_n(t) \) are the measured distance and the real distance between the mobile station and the base station at time \( t \). \( N_n(t) \) is non-line-of-sight error, \( i_n(t) \) is measurement error, \( f_n(t) \) is system error.

Obviously, in practical application, the traditional Kalman filter algorithm is no longer suitable to deal with NLOS error and measurement error existing in practice. Therefore, the state equation of the extended Kalman filter is established, and its space model is described as follows:

\[ X_k = \Phi_{k-1}X_{k-1} + \Gamma_{k-1}W_{k-1} \]

(2)

\[ \Delta Z_k = H_k X_k - H_k X_{k-1} + V_k \]

(3)

In the formulas above, \( X_k \) is the target state at time \( k \), \( \Delta Z_k \) is Increment of measurement, \( \Phi_{k-1} \) is state transition matrix, \( H_k \) is measurement matrix and \( \Gamma_{k-1} \) is noise driven matrix. \( W_k \) and \( V_k \) are unrelated. Their variances are going to be \( Q_k \) and \( R_k \).

In the process of measurement:

\[ \Delta Z_k = Z_k - Z_{k-1} = h_k(X_k) - h_{k-1}(X_{k-1}) + v_k - v_{k-1} + V_k \]

(4)

Due to the high sampling frequency of UWB signal, \( v_k - v_{k-1} \) is a relatively small quantity. So it's negligible. Therefore, this model can effectively eliminate the unknown system error. The iterative equation of the extended incremental Kalman filter is shown as follows.

\[ \tilde{X}_{k}(k-1) = f_{k-1}(\tilde{X}_{k-1}) \]

(5)

\[ P_{k}(k-1) = \Phi_{k-1}P_{k-1}\Phi^T_{k-1} + \Gamma_{k-1}Q_{k-1}\Gamma^T_{k-1} \]

(6)

\[ \tilde{X}_k = \tilde{X}_k(k-1) + K_k(\Delta Z_k - \Delta \tilde{Z}_k(k-1)) \]

(7)

\[ P_k = P_{k}(k-1) - K_k\Omega_kK^T_k \]

(8)

\[ K_k = (H_kP_{k-1}\Phi^T_{k-1} - \Phi_{k-1}P_{k-1}H^T_k)\Omega_k^{-1} \]

(9)

\[ \Omega_k = H_kP_{k}(k-1)H^T_k + H_kP_{k-1}\Phi^T_{k-1} - H_kP_{k-1}\Phi_{k-1}H^T_k + H_kP_{k-1}P_{k-1}H^T_k \]

(10)

In the iterative process of Kalman filter, based on the non-negative property of the non-horizon error, the possible negative NLOS estimation value is set to zero. The NLOS error estimate is then obtained. Further, accurate distance between two points can be obtained.

3. CHAN Location Algorithm

In the UWB positioning, we obtain the measured value of TDOA, and then we can get the distance difference between the mobile station and the two base stations. Multiple measurements can be used to obtain hyperbolic equations, which can be solved to obtain the estimated position of MS. Let \( (x, y) \) be the position of MS. \( (x_i, y_i) \) is the known location of the base station \( i \). Then the distance between MS and the ith base station is \( R_i = \sqrt{(x_i - x)^2 + (y - y_i)^2} \).

\[ R_i^2 = K_i - 2x_ix_i - 2y_iy_i + x^2 + y^2 \]

(12)

In the formula above, \( K_i = x^2 + y^2 \). \( R_{i1} \) is the distance difference between MS and the ith base station and the first base station. And \( R_{i1} = \sqrt{(x_i - x)^2 + (y - y_i)^2} - \sqrt{(x_1 - x)^2 + (y - y_1)^2} \).

\[ R_{i1}^2 + 2R_{i1}R_i + R_i^2 = K_i - 2x_iy_i - 2y_iy_i + x^2 + y^2 \]

(13)

At \( i = 1 \), \( R_1^2 = K_1 - 2x_1y_1 - 2y_1y_1 + x^2 + y^2 \).

\[ (13)-(14) = R_{i1}^2 + 2R_{i1}R_1 = K_1 - 2x_1y_1 - 2y_1y_1 - K_1 \]

(15)
In the formula above, \( x_{i,1} = x_i - x_1 \), \( y_{i,1} = y_i - y_1 \). It can be seen from the above equation that the equation can be transformed into linear equations for \( x \), \( y \) and \( R \), when \( R \) is taken as an unknown quantity.

When the number of base stations is 3, two hyperbolic equations can be obtained. By solving these two equations, the solution of two unknowns can be obtained, and this is the position of MS.

When the number of base stations is 4 or more and MS is long distance, its position estimate is

\[
Z_{ij} = \sqrt{(G_{ij}Q^{-1}G_i)^{-1}G_{ij}Q^{-1}h}.
\]

When \( Z_{ij} \) is the coordinate value difference between the \( i \)th base station and the first base station. \( R_{ij} \) is the distance difference between MS and the \( i \)th base station and the first base station.

\[
G_a = \begin{bmatrix}
  x_{2,1} & y_{2,1} & R_{2,1} \\
  x_{3,1} & y_{3,1} & R_{3,1} \\
  x_{m,1} & y_{m,1} & R_{m,1}
\end{bmatrix}
\]

\[
h = \frac{1}{2} \begin{bmatrix}
  R_{2,1}^2 - x_2^2 - y_2^2 + x_1^2 + y_1^2 \\
  R_{3,1}^2 - x_3^2 - y_3^2 + x_1^2 + y_1^2 \\
  R_{m,1}^2 - x_m^2 - y_m^2 + x_1^2 + y_1^2
\end{bmatrix}
\]

\( Q \) is the covariance matrix of TDOA. \( \{x_{i,1}, y_{i,1}\} \) is the coordinate value difference between the base station and the first base station. \( R_{i,1} \) is the distance difference between MS and the \( i \)th base station and the first base station.

4. BP neural network algorithm

In the NLOS environment, the measured value of TDOA may have a large error. Even if the filtering algorithm has been improved to a certain extent, it will still have a great impact on the CHAN algorithm, and the calculated coordinates will still be significantly different from the actual coordinates. Neural network algorithm has many good characteristics, such as good adaptive ability and large-scale parallel processing ability [8]. Therefore, this algorithm can effectively reduce the non-line-of-sight error of TDOA measurements and effectively improve the positioning accuracy of the system. BP neural network algorithm is used in this paper. BP neural network is a three-layer network. It includes input layer, hidden layer and output layer respectively [9].

The transfer function of BP neural network is differentiable. Generally known as linear functions or S-type functions, S-type functions can be divided into two types, namely, the Tan-Sigmoid function and the Log-Sigmoid function. The choice of S-type function depends on whether the output contains negative values. Tan-Sigmoid is

\[
f_1(x) = \frac{1}{1 + e^{-x}}
\]

and Log-Sigmoid function is

\[
f_2(x) = \frac{e^x - e^{-x}}{e^{x} + e^{-x}}.
\]

In this algorithm, the input of the neural network is \( P_i = [x_1, x_2] \) and the output is \( a_{2k} = [y_1, y_2] \). Therefore, the number of neurons in the input layer is 2, the number of neurons in the hidden layer is set as \( n \), and the activation function between the input layer and the output layer is represented by \( f_1(x) \). The connection weight and deviation between the input layer and the output layer are represented by \( \omega_{ij} \) and \( b_{li} \) respectively. Therefore, the output of the \( i \)th neuron in the hidden layer is

\[
a_{li} = f_1(\sum_{j=1}^{n} \omega_{ij}p_j + b_{li}), \quad i = 1,2, \ldots, n.
\]

The number of neurons in the output layer is 2, and the activation function between the input layer and the output layer is represented by \( f_2(x) \). The connection weight between the input layer and the output layer is expressed by \( \omega_{ki} \), and the deviation is expressed by \( b_{2k} \). Therefore, the output of the \( k \)th neuron in the output layer is

\[
a_{2k} = f_2(\sum_{i=1}^{n} \omega_{ki}a_{li} + b_{2k}) \quad k = 1,2.
\]

The loss function is

\[
E = \frac{1}{2} \sum_{k=1}^{2}(t_k - a_{2k})^2.
\]

Since \( E \) is a function of the weights \( \omega_{ij} \) and \( \omega_{ki} \), the weight can be adjusted using the gradient descent algorithm to reduce the value of \( E \) of the loss function. According to the gradient
descent method, for learning efficiency $\eta$, the weight changes are shown as follows.

$$
\Delta \omega_{kl}(t) = -\eta \frac{\partial E}{\partial \omega_{kl}} = -\eta \frac{\partial E}{\partial a_{2k}} \frac{\partial a_{2k}}{\partial \omega_{kl}} = \eta (t_k - a_{2k}) f'_2 a_{1i} \tag{20}
$$

$$
\Delta \omega_{ij}(t) = -\eta \frac{\partial E}{\partial \omega_{ij}} = -\eta \frac{\partial E}{\partial a_{2k}} \frac{\partial a_{2k}}{\partial a_{1i}} \frac{\partial a_{1i}}{\partial \omega_{ij}} = \eta \sum_{k=1}^{2} (t_k - a_{2k}) f'_2 \omega_{ki} f'_1 p_j \tag{21}
$$

$$
\omega_{kl}(t + 1) = \omega_{kl}(t) + \Delta \omega_{kl}(t) \tag{22}
$$

$$
\omega_{ij}(t + 1) = \omega_{ij}(t) + \Delta \omega_{ij}(t) \tag{23}
$$

After training the BP neural network model according to the above process, the final result of the algorithm is $\{y_1, y_2\} = sim(net, [x_1, x_2])$. \tag{24}

5. Experiment and Simulation

The test site is selected in an open area, and there is a part of shielding which will cause non-line-of-sight error. UWB positioning base station is the core part of the positioning module, the main function is to complete the ranging work with the label. UWB positioning base station is mainly composed of DW1000 positioning chip, 5G-WIFI module, wireless network card and the corresponding peripheral circuit.

In the test process, the label is guaranteed to advance at a uniform speed along the specified route, and the process noise and measurement noise are assumed to be Gaussian distribution with zero mean value. As can be seen from Figure 1 and Figure 2, after the compensation by the extended incremental Kalman filter and BP neural network algorithm, the fluctuation value of distance decreases a lot. Compared with the ordinary Kalman filter algorithm, the algorithm adopted in this paper greatly reduces the non-line-of-sight error and the systematic error caused by the measurement equation, and the deviation from the true value is reduced, thus improving the positioning accuracy.

![Figure 1. Label coordinates change before and after filtering](image_url)
6. Conclusion
In this paper, the extended incremental Kalman filter algorithm and BP neural network algorithm are used to eliminate the non-line-of-view error and the system error caused by the measurement equation in the process of UWB positioning. Through experiment and simulation, the feasibility of the proposed algorithm is verified, and the positioning accuracy is significantly improved.

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