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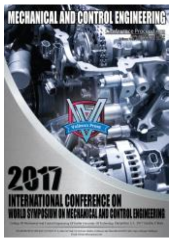

APPLICATION OF INDOOR POSITIONING BASED ON KPCA AND BP NEURAL NETWORK ALGORITHM

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ABSTRACT

As the location method of indoor fingerprint position needs to be conducted in a region with signal coverage, the signal intensity's information of all Access Points has to be collected to build a fingerprint database. And not all information in the database will be of positive service to the positional accuracy. On account of increasing data dimensions in the database, rising complexity of algorithm and the climbing number of required experimental samples, a dimension disaster could be arisen. Based on KPCA algorithmic method, in this paper, positioning performance will be improved even under noisy circumstance by preprocessing the position fingerprint data and some data space occupied by positioning system will be saved through decreasing the data dimensions and reduced information of redundancy.

1. INTRODUCTION

With the rapid development of social economy, location-based applications play an increasingly important role. Such as emergency rescue, vehicle tracking, positioning and navigation, museum guides, shopping guide, etc., has a very broad application prospects. In the wireless sensor network positioning, positioning technology can be divided into two categories: positioning based on range free technique and based on ranging technology [1]. Based on range free positioning technologies including DV-Hop, Centroid location and APIT location [2-4]. These algorithms only need to locate the nodes according to the connectivity of the network, the localization precision is low; The localization of ranging technology mainly includes AOA(angle of arrival), TOOA(time of arrival), TDOA (time difference of arrival) and based on RSSI [5-7]. These algorithms need to measure the distance or angle information between the nodes to be located and anchor nodes to achieve the location.

In the actual indoor environment, due to the interference of many environmental factors such as reflection, refraction, multipath propagation and obstacle blockage, the time variation of the Received Signal Strength Indication (RSSI) of the node to be located is so strong, this leads to the uncertainty of the parameter A and the path loss factor n in the signal model, and finally it is applied to the positioning algorithm, which makes the positioning error larger [8]. To solve this problem, this paper adopts the indoor positioning algorithm based on BP neural network, uses BP neural network to learn the relationship between RSSI and distance d, and avoids the determination of parameters A and n in complex indoor environment, thus improving the positioning accuracy [9]. In addition, due to the use of BP neural network algorithm, often need to collect the positioning area of each AP signal intensity value, if the number of AP is more likely to lead to the information dimension is too high, the number of training samples rise. Kernel Principal component analysis (KPCA) feature extraction algorithm is proposed in this paper, the feature information of position fingerprint map can be extracted from a large number of environmental noise by using nuclear technology, which can reduce the influence of noise on positioning performance and improve the positioning accuracy to some extent [10].

2. DATA PREPROCESSING BASED ON KPCA

Kernel principal component analysis method combines the characteristics of principal component analysis and the advantages of kernel method. by processing the location fingerprint image, it can restrain the influence of environmental noise to some extent, save the terminal storage space and improve the system performance [11]. Similar to principal component analysis, kernel principal component analysis can first map the nonlinear location fingerprint data set into high-dimensional space by kernel method, and then the principal component analysis in high-dimensional space can effectively solve the problem that the nonlinear data set is difficult to be classified in linear space.

2.2 Application principle of kernel principal component analysis algorithm

The flow of applying KPCA in indoor positioning system is as follows:
Define the non-linear mapping $\delta : R^M \to f$，Among them, R^M is the reference point (receive RSS data from M AP, Φ is M dimension vector) belongs to the European space, f is the Hilbert functional space (high dimensional feature space), and the inner product operation of this space can be calculated by kernel function. In the process of principal component analysis, the original data set needs to be centralized in advance to generate a covariance matrix:

$$C = \frac{1}{N}\sum_{j=1}^{N}(\Phi_j^*)^T \cdot \Phi_j^* \qquad (1)$$

In the kernel principal component analysis method, the covariance matrix between the reference samples is mapped into the high-dimensional feature space:

$$\bar{C} = \frac{1}{N}\sum_{i=1}^{N}\delta^T(\Phi_i^*)\delta(\Phi_i^*), i = 1,2,3,\dots,N \qquad (2)$$

The definition $\bar{\varepsilon}$ is the eigenvalue of covariance matrix $\bar{C}$, and $\bar{V}$ is the eigenvector corresponding to the eigenvalue:

$$\bar{\varepsilon}\bar{V} = \bar{C}\bar{V} \qquad (3)$$

The covariance matrix belongs to the high-dimensional feature space, although the dimension cannot be determined, it can be proved that the feature vector must be in the space of the sample. Such as the principal component analysis, the covariance matrix of the position fingerprint data set is shown as (1), and its generalized eigen decomposition:

$$\varepsilon_i V_i = CV_i = \left(\frac{1}{N}\sum_{j=1}^{N}(\Phi_j^*)^T \cdot \Phi_j^*\right)V_i = \frac{1}{N}\sum_{j=1}^{N}(\Phi_j^{*T}V_i)\Phi_j^* \qquad (4)$$

$$\therefore V_i = \frac{1}{\varepsilon_i N}\sum_{j=1}^{N}(\Phi_j^{*T}V_i)\Phi_j^* \qquad (5)$$

Where $\Phi_j^{*T}V_i$ is a scalar, if the parameter$\alpha_j^i = \Phi_j^{*T}V_i/\varepsilon_i$, then?

$$V_{\mathrm{i}} = \sum_{j=1}^{N}\alpha_j^i\Phi_j^* \qquad (6)$$

It is proved that the eigenvector $V_i$belongs to the space formed by the data set$\{\Phi_1^*,\Phi_2^*,\Phi_3^*,\ldots,\Phi_j^*,\Phi_N^*\}$, Therefore, in the Kernel Principal Component Analysis method, eigen vector $V_i \in span\{\Phi_1^*,\Phi_2^*,\Phi_3^*,\ldots,\Phi_j^*,\Phi_N^*\}$. There are: $\bar{V} \in span\{\delta_1^*,\delta_2^*,\delta_3^*,\ldots,\delta_j^*,\delta_N^*\}$

$$\bar{V} = \sum_{j=1}^{\mathrm{N}}\alpha_j\delta(\Phi_j^*) \qquad (7)$$

The formula (7) is substituted in (3), and the left multiplication $\delta^T(\Phi_j^*)$ ，$\mathrm{i} = 1,2,3,\ldots,\mathrm{N}$ is used to construct inner product:

$$\bar{\varepsilon}\sum_{j=1}^{\mathrm{N}}\alpha_j\delta^T(\Phi_j^*)\delta(\Phi_j^*) = \delta^T(\Phi_i)\cdot\frac{1}{N}\sum_{l=1}^{\mathrm{N}}\delta^T(\Phi_j^*)\delta(\Phi_j^*)\cdot\sum_{j=1}^{\mathrm{N}}\alpha_j\,\delta(\Phi_j^*) \qquad (8)$$

Among them, $\mathrm{i,j,l} = 1,2,3,\ldots,\mathrm{N}$,Since kernel function can replace inner product operation in high-dimensional space, that is: $K_{ij} = K(\Phi_i^*,\Phi_j^*) = \delta^T(\Phi_i^*)\cdot(\Phi_j^*)$，Then (8) can be expressed as:

$$\bar{\varepsilon}\left(\sum_{j=1}^{N}\alpha_{jK_{ij}}\right) = \frac{1}{N}\sum_{l=1}^{N}\sum_{j=1}^{N}\alpha_j K_{li}\,K_{jl} \qquad (9)$$

Let $\mathrm{K} = [K(\Phi_i^*,\Phi_j^*)]_{NxN}$ ， $\alpha = (\alpha_1,\alpha_2,\ldots,\alpha_N)^T$, Formula (9) can be simplified as:

$$\bar{\varepsilon}(\mathrm{K}\alpha) = \frac{1}{N}(K^2\alpha) \qquad (10)$$

Can get:

$$\bar{\varepsilon}\alpha = \mathrm{K}\alpha \qquad (11)$$

Among them $\tilde{\varepsilon} = \mathrm{N}\bar{\varepsilon}$,obviously, the problem of eigenvalue decomposition for seeking the covariance matrix $\bar{C}$in high-dimensional space has been transformed into the eigenvalue problem. $\tilde{\varepsilon}_1,\tilde{\varepsilon}_2,\tilde{\varepsilon}_3,\ldots,\tilde{\varepsilon}_N$ and $\alpha_1,\alpha_2,\alpha_3,\ldots,\alpha_N$ are the eigenvalues and eigenvectors of matrix K.. Therefore, the i eigenvalues and eigenvectors of the covariance matrix C are:

$$\bar{\varepsilon}_i = \frac{\bar{\varepsilon}_i}{N} \text{，} \bar{V}_i = \sum_{j=1}^{N}\alpha_j^i\delta(\Phi_j^*) \qquad (12)$$

Among them, α_{j}^i is the j element ofα_i.Therefore, through the center location fingerprint processing, arbitrary projection data points in high dimensional feature space in i direction can be expressed as:

$$\delta(\Phi^*)^T\bar{V}_i = \sum_{j=1}^{N}\alpha_j^i\delta^T(\Phi^*)\delta(\Phi_j^*) = \sum_{j=1}^{N}\alpha_j^i K(\Phi^*,\Phi_j^*) \qquad (13)$$

By selecting the largest first d eigenvalues $\bar{\varepsilon}_1,\bar{\varepsilon}_2,\bar{\varepsilon}_3,\ldots,\bar{\varepsilon}_d$, and corresponding eigen vectors$\bar{\mathrm{V}}_1,\bar{\mathrm{V}}_2,\bar{\mathrm{V}}_3,\ldots,\bar{\mathrm{V}}_d$，$\mathrm{d} \ll \mathrm{M}$,a low dimensional embedding method for data sets can be obtained: $\bar{\mathrm{V}} = (\bar{\mathrm{V}}_1,\bar{\mathrm{V}}_2,\bar{\mathrm{V}}_3,\ldots,\bar{\mathrm{V}}_d)$,the original location fingerprint data set can be transformed into a feature fingerprint map. Similarly, in the online stage of the indoor positioning process, the user receives a set of RSS values at any point, firstly, the low-dimensional embedding calculation (operation d times through (13)) to obtain a d-dimensional eigenvector, and then through the matching algorithm and feature location fingerprints Φ^{d} ($\mathrm{N}\times\mathrm{d}$ dimensional data set) to compare and calculate, the final position coordinates is obtained.

2.3 KPCA algorithm flow chart

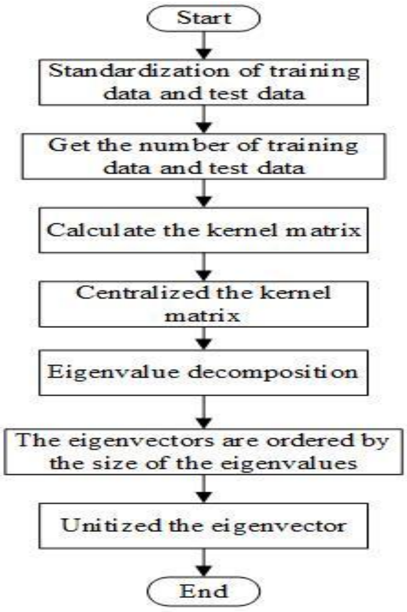

Figure 1: KPCA algorithm flow chart

3. Indoor location algorithm based on BP neural network

3.2 BP neural network positioning model

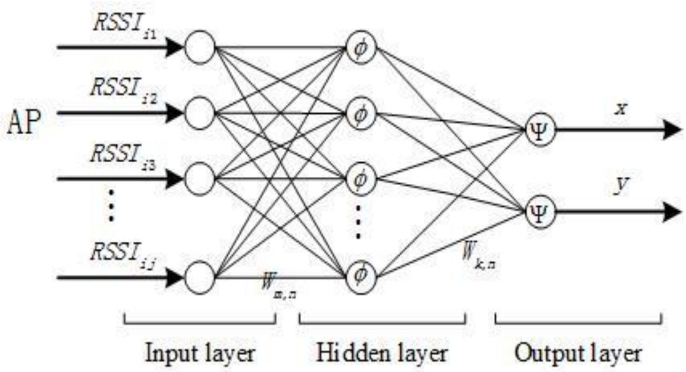

Figure 2: BP neural network positioning model

Figure 2 is a three-layer feedforward neural network, the input vector matrix$RSSI_i$ $(i = 1,2,3,\cdots,N)$represents a reference node to obtain n of RSSI value, the hidden layer and the output layer are ϕ and Ψ excitation functions; The input layer to the hidden layer weight adjustment vector is W_{mn}. The weight adjustment vector from the hidden layer to the output layer is $W_{k,n}$.

3.3 Weight adjustment

In the BP neural network, the error signal reverse transfer sub-process is more complex, it is based on Widrow-Hoff learning rules. Suppose that all the results in the output layer are $d_j$and the error function is as follows

$$E(w,b) = \frac{1}{2}\sum_{j=0}^{n-1}(d_j - y_j)^2 \qquad (14)$$

The main purpose of BP neural network is to revise the weights and thresholds repeatedly, so that the error function value is minimum. The Widrow-Hoff learning rule adjusts the weights and thresholds of the network continuously by steepest descent direction along the sum of squares of the relative error. According to the gradient descent method, the correction of the weight vector is proportional to the gradient of the $E(w,b)$ at the current position, and has the j output node

$$\Delta w(i,j) = -\eta\frac{\partial E(w,b)}{w(i,j)} \qquad (15)$$

Suppose that the activation function is chosen as

$$f(x) = \frac{A}{1+e^{-\frac{\infty}{B}}} \qquad (16)$$

The derivative of activation function is obtained

$$f'(x) = \frac{Ae^{-\frac{\infty}{B}}}{B\left(1+e^{-\frac{\infty}{B}}\right)^2} = \frac{1}{AB}\cdot\frac{A}{1+e^{-\frac{\infty}{B}}}\cdot\left(A-\frac{A}{e^{-\frac{\infty}{B}}}\right) = \frac{f(x)[A-f(x)]}{AB} \quad (17)$$

So next for w_{ij}

$$\frac{E(w,b)}{\partial w_{ij}} = \frac{1}{\partial w_{ij}}\cdot\frac{1}{2}\sum_{j=0}^{n-1}(d_j-y_j)^2 = (d_j-y_j)\cdot\frac{d_{ij}}{w_{ij}} = (d_j-y_j)\cdot f'(S_j)\cdot\frac{\partial s_j}{\partial w_{ij}} = (d_j-y_j)\cdot\frac{f(s_j)[A-f(s_j)]}{AB}\cdot\frac{\partial s_j}{\partial w_{ij}} = (d_j-y_j)\cdot\frac{f(s_j)[A-f(s_j)]}{AB}\cdot x_i = \delta_{ij}\cdot x_i \quad (18)$$

$$\delta_{ij} = (d_j-y_j)\cdot\frac{f(s_j)[A-f(s_j)]}{AB} \quad (19)$$

Same for b_j

$$\frac{\partial E(w,b)}{\partial b_j} = \delta_{ij} \quad (20)$$

This is the well-known δ-learning rule, which reduces the error between the actual output of the system and the expected output by changing the connection weights between neurons. This rule is also called Widrow-Hoff learning rule or error correction learning rule.

With the above formula, according to the gradient descent method, then the weights and thresholds of the neural network are adjusted as follows

$$w_{ij} = w_{ij} - \eta_1\cdot\frac{\partial E(w,b)}{\partial w_{ij}} = w_{ij} - \eta_1\cdot\delta_{ij}\cdot x_i \quad (21)$$

$$b_j = b_j - \eta_2\cdot\frac{\partial E(w,b)}{\partial b_j} = b_j - \eta_2\cdot\delta_{ij} \quad (22)$$

2.3 KPCA combined with BP neural network indoor positioning algorithm flow chart

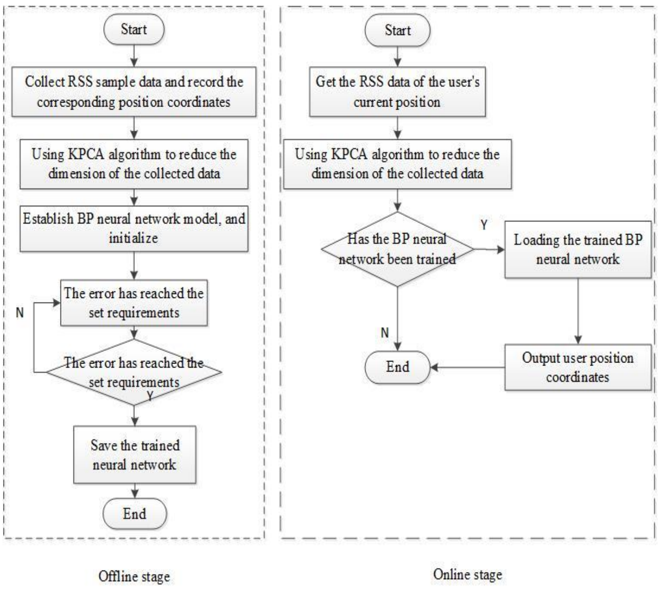

Figure 3: KPCA combined with BP neural network indoor positioning algorithm flow chart

As shown in the flow chart of Figure 3, indoor positioning can be divided into two stages: offline stage and online stage, the offline phase includes data acquisition, using the KPCA algorithm to reduce the dimension of the collected data, neural network model establishment and training as well as save a trained neural network. The online stage includes real-time data acquisition and data input into the saved neural network for positioning.

4. SIMULATION EXPERIMENT

In this paper, an indoor environment of 6m*10m is selected as the positioning area for this experiment. A target node is set every 2m on both sides of the positioning area, and a total of 12 target nodes are set. The coordinates of the target node are(0,0),(2,0),(4,0),(6,0),(8,0), （10,0） ,(0,6),(2,6） ,(4,6),(6,6),(8,6),(10,6).The RSSI values of each target node are collected at the distance from the target node 2m, and the RSSI values and position coordinates are collected into the established database. Matlab is used to write the KPCA algorithm to reduce the dimension of the collected RSSI, and then as the input of the BP neural network, the position coordinate is used as the output of the neural network. The neural network is trained to output the positioning results, and the results are compared.

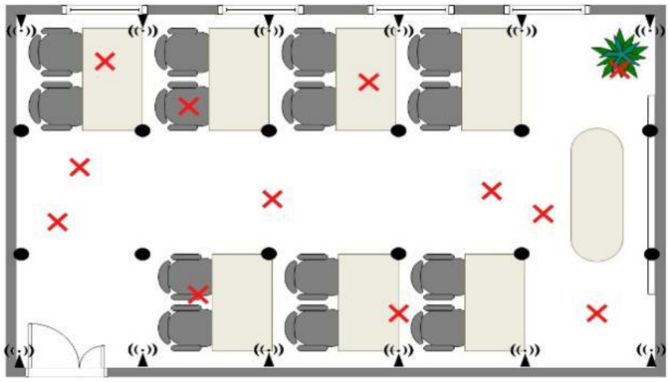

Figure 4: KPCA combined with BP neural network localization results

In the graph, represents the location of the target node, represents the coordinate position of the reference node, and represents the positioning result of the KPCA combined with the BP neural network.

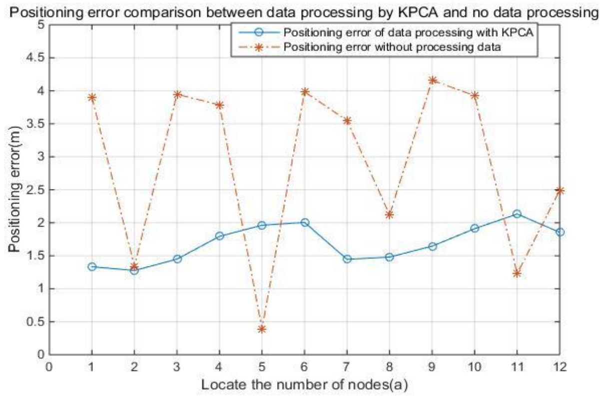

Figure 5: Data preprocessing and no processing error comparison

It can be seen from Figure 5 that the KPCA algorithm is used to preprocess the data, the error of positioning result is about 1.5m, if the data is not preprocessed, it is directly input into the BP neural network, the positioning error is within 0.4m~4.2m, and the positioning error is larger.

5. CONCLUSION

In this paper, when using BP neural network for indoor positioning, the dimension disaster caused by excessive target node, KPCA algorithm is used to preprocess the collected data, the experimental results show that using KPCA algorithm to preprocess the data can effectively improve BP neural network positioning accuracy.

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