International Journal of Future Generation Communication and Networking
Vol. 9, No. 3 (2016), pp. 201-214
http://dx.doi.org/10.14257/ijfgcn.2016.9.3.19

Study of Indoor Positioning Method Based on Combination of Support Vector Regression and Kalman Filtering

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Abstract

Against the problem that indoor positioning suffers quite large errors and irregular user location movement, this paper adopts Support Vector Regression (SVR) for initial positioning and Kalman filtering for filtering of the positioning results so as to improve the accuracy of the positioning system. The experimental results show that against the real WLAN environment, SVR positioning results processed by Kalman filtering indicates the root mean square error is decreased by 16%, and 73% of positioning accuracy within 2 meters is increased to 83%.

Keywords: *Indoor positioning; SVR; Kalman filtering; positioning accuracy*

1. Introduction

With the rapid development of mobile communication technology, Location Based Services (LBS), a location-based and service-oriented technology came into being and quickly gained widespread attention of the community, which reflects the importance of its core technology – positioning [1][2]. So far, the outdoor positioning technology has been relatively mature, focusing on the global positioning system, such as GPS, GLONASS and Beidou satellite navigation and positioning systems to achieve all-weather real-time positioning. In terms of study and utilization of outdoor GPS positioning technology, research on the indoor positioning technology started late, and the current indoor positioning focuses on positioned based on WLAN signal strength, utilizing the correlation of the existing indoor Received Signal Strength (RSS) signal and position information to achieve positioning[3-6]. Currently, RSS-based indoor positioning algorithms mostly adopt the position fingerprint technology [7-10]. Different from the positioning technology based the signal time of arrival (TOA) and angle of arrival (AOA) [11, 12], fingerprint positioning does not require any additional hardware to develop precise time synchronization or angular measurements. It can take advantage of existing wireless network infrastructure, greatly reducing the cost of the system and achieving a wide range of applicability. Location fingerprinting algorithms can be divided into two phases: Offline and online phases. In the offline phase, it is necessary to select a number of reference points and collect RSS at each reference point position corresponding to multiple Access Point (AP), establishing database storing each reference point location and fingerprint corresponding to RSS. In the online phase, it is necessary to compare RSS obtained in the terminal real time measurement with RSS in the fingerprint data, estimating the position of the terminal. Traditional online matching algorithms include K Nearest Neighbor (KNN) [13], Support Vector Machine (SVM) [14] and probability distribution [15].

In case of real-time follow-up applications, the system shall calculate the user's current location within a short time to achieve real-time, resulting in less samples of the signal strength obtained by the terminal. In addition, affected by uncertainties in the surrounding environment, the signal may witness greater fluctuation in a short time. These two factors

ISSN: 2233-7857 IJFGCN

will reduce the positioning accuracy of the system. Therefore, calculating the user's position directly with the conventional positioning algorithm makes user's location characterized by a large variance in the user's location and irregular user's mobile position and significant jump, seriously affecting the indoor positioning system's performance and stability. To solve the above problem, this paper proposes the SK algorithm combining SVR and Kalman Filtering, firstly applying SVR algorithm to obtain the location coordinates to be determined, then applying Kalman Filtering to filter the user's location coordinates estimated by positioning algorithm, making the user's location movement regular to improve the positioning accuracy of the indoor positioning system. Simulation and real experimental results show that the filtered position is significantly improved.

2. Related Work

Many position technologies and applications have been proposed. Microsoft research first proposed the indoor position system RADAR based on WLAN, which takes the RSS as character parameter of position and uses the K-nearest neighbor (KNN) to realize position match [16]. In open indoor environment, the system can obtain accuracies of 2-3 meters, using 70 access points that are placed non-uniformly at least 2.5 meters, but accuracy is not ideal in complex indoor environment.

In 2002, Horus system models the probability statistic, and stores the RSS Gaussian distribution in radio map [17]. At the same time, the block cluster concept first is proposed. The system decreases computational complex and improves positioning accuracy compared to the others.

Ekahau is a real-time position system that localizes the position of terminal based on statistic conditional probability by comparing the different between the received signal RSS and radio map [18]. The positioning accuracy of the system can achieve 1meter.

With the application of new algorithms and new theory in WLAN indoor position area, many advanced WLAN position systems come up. For example, a position method is proposed based on manifold regularization by J.J. Pan, *et. al.* [19]. The system that utilizing the RSS sample both of labeled position coordinate and unlabeled position coordinate is different from conditional WLAN indoor position system. The method is a two-step procedure. The first step, which is generally carried out offline, is the collection and process part labeled RSS sample, then computes the figure Laplace matrix. Finally, an estimation function of position coordinate is obtained by training using the above matrix and manifold learning theory. The second step firstly preprocesses unlabeled online RSS data, and position result is obtained through putting the processed date into estimation function.

3. SVR Location Algorithm

Based on the structural risk minimization theory, the support vector machine (SVM) learning machine comprehensively considers learning function VC dimension and training errors, seeking the learning functions minimizing the actual risks so as to improve the generalization capacity of the learning machine. It has multiple unique advantages in nonlinear and high dimensional pattern recognitions. SVM can be divided into support vector classification (SVC) and support vector regression (SVR). SVR function regression has been successfully applied to the system identification and nonlinear system prediction.

3.1. Overview

This paper SVR positioning includes offline and online phases:

(1) Offline phase:

In the offline phase, it is necessary to utilize a mobile device to collect original training data sets consisting of RSS information from each AP at the known reference points of the pre-selected position coordinates. Considering the indoor environment is usually complex, witnessing different factors significantly impacting RSS signal distribution such as wall reflections and people walking, it is necessary to filter the original training data sets so as to achieve higher reliability of the data sets and properly characterize RSS distribution against the indoor wireless environment. After filtration, the data sets are taken as input conditions and SVR is utilized for supervised learning so as to achieve the corresponding position prediction model.

(2) On-line phase:

In the on-line phase, it is necessary to utilize a mobile device to collect ambient wireless signals at the position points of the unknown coordinates and obtain a RSS data set. It is necessary to filter the data set by the means similar to that of the offline phase. The position prediction model made in the offline phase and the RSS data sets obtained in the online phase are utilize to predict obtained RSS data sets location prediction and obtain the position coordinates of the indoor mobile targets.

3.2. Location Prediction Model

Position prediction model describes the physical location of the mobile device and the relationship between it and RSS information received from adjacent wireless access points. Suppose there are n AP and N reference points in the positioning system, RSS information received by the mobile device at Position A is $s_A = \{rss_A^1, rss_A^2, \cdots, rss_A^n\}$, rss_A^i is RSS of No. i wireless access point received by the mobile device at Position A, is the position coordinates of the mobile device at Position A, the given data set $D := \{(s_i, L_i)\}_{i=1}^N (s_i \in R, L_i \in L)$, the target of function regression theory is to seek mapping $f : R \to L$: achieving $f(s_i) \approx L_i$. The mapping relationship belongs to non-linear mapping relationships. Based on the support vector machine method, in terms of nonlinear, it is proper to utilize nonlinear function $\Phi(s)$ to project the input space R into the high dimensional feature space $R^{'}$, and utilize the linear function to fit the data set $\{(\Phi(s_i), L_i)\}_{i=1}^N$ in the high dimensional feature space:

$$L = f(s) = W^T \Phi(s) + b \tag{1}$$

Where $W \in R^{'}$ is weight vector, b is bias term.

According to the statistics theory, it is proper to calculate take the following objective function (training error function) minimum value and obtain W, b :

$$J(w) = \frac{1}{2}\|w\|^2 + \lambda \sum_{i=1}^{N} | L_i - (W^T \Phi(s) + b) |_{\varepsilon} \tag{2}$$

Where ε, λ is the empirical parameter, $\left| L_i - (W^T \Phi(s) + b) \right|_{\varepsilon}$ is called ε insensitive loss function, the value taking is as follows:

$$\left| L_i - (W^T \Phi(s) + b) \right|_{\varepsilon} = \begin{cases} 0, & \left| L_i - (W^T \Phi(s) + b) \right| < \varepsilon \\ L_i - (W^T \Phi(s) + b) - \varepsilon, & else \end{cases} \tag{3}$$

That is, when the error of the predicted value is less than ε , the loss function value is taken as 0; otherwise, the linear punishment shall be taken.

Introduce two slack variables ξ_i , $\xi_i^{'}$, equivalent to the following optimization, achieving:

$$\min \frac{1}{2}\|w\|^2 + C\left(\sum_{i=1}^{N}(\xi_i + \xi_i^{'})\right) \tag{4}$$

$$\text{s. t.}\begin{cases} L_i - (W^T\Phi(s)+b) \le \varepsilon + \xi_i \\ (W^T\Phi(s)+b-L_i) \le \varepsilon + \xi_i^{'} \\ \xi_i \ge 0 \\ \xi_i^{'} \ge 0 \end{cases}$$

Parameter ε indicates the requirement of the system for regression function error on the training data set error, the smaller ε is, the smaller the error of the regression function on the training data set will be and the higher the obtained regression function estimation accuracy will be and the more the support vectors will be. Parameter C is the punishment to the data set on the training data set with the regression estimated function error greater than ε, the greater C is, the greater the punishment to these data sets will be.

The above optimization can be defined as the following lagrangian function:

$$L(w,\xi_i,\xi_i^{'}) = \frac{1}{2}\|w\|^2 + C\left(\sum_{i=1}^{N}(\xi_i + \xi_i^{'})\right) - \sum_{i=1}^{N}(\eta_i\xi_i + \eta_i^{'}\xi_i^{'}) -$$

$$\sum_{i=1}^{N}\alpha_i(W^T\Phi(s_i) - L_i + \varepsilon + \xi_i) - \sum_{i=1}^{N}\alpha_i^{'}(L_i - W^T\Phi(s_i) + \varepsilon + \xi_i) \tag{5}$$

Where $\xi_i, \xi_i^{'}, \alpha, \alpha^{'}$ is lagrangian multiplier, when it acquires extremes, it is necessary to achieve

$$\frac{\partial L(w,\xi_i,\xi_i^{'})}{\partial w} = w - \sum_{i=1}^{N}(\alpha_i - \alpha_i^{'})\Phi(s_i) = 0$$

$$\frac{\partial L(w,\xi_i,\xi_i^{'})}{\partial \xi_i} = \eta_i - (C - \alpha_i) = 0$$

$$\frac{\partial L(w,\xi_i,\xi_i^{'})}{\partial \xi_i^{'}} = \eta_i^{'} - (C - \alpha_i^{'}) = 0$$

Make the above three formulas into the formula, and introduce kernel function $K(s_i, s_j)$ based on the SVR theory and utilize Wlofe dual techniques to transfer the above into the following corresponding dual optimization, achieving:

$$\min \sum_{i=1}^{N} L_i(\alpha - \alpha_i^{'}) - \varepsilon\sum_{i=1}^{N}(\alpha_i - \alpha_i^{'}) - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i - \alpha_i^{'})(\alpha_j - \alpha_j^{'})K(s_i, s_j) \tag{6}$$

$$\text{s. t.}\begin{cases}\sum_{i=1}^{N}(\alpha_i-\alpha_i^{'})=0\\0\le\alpha_i\le C\\0\le\alpha_i^{'}\le C\end{cases}$$

Thus, the corresponding regression formula can be changed to the following formula:

$$L=\sum_{i=1}^{N}(\alpha_i-\alpha_i^{'})K(s,s_i)+b \tag{7}$$

This paper adopts RBF core $K(s_i,s_j)=\exp\left(-\frac{\left\|s_i-s_j\right\|^2}{2\sigma^2}\right)$.

4. Kalman Filtering Algorithm

In real-time positioning system, it is necessary to calculate the user's position in a short period of time, which usually suffers small signal samples and large positioning errors. This paper proposes Kalman Filtering SVR positioning results SK algorithm so as to reduce SVR positioning errors and improve positioning accuracy.

Kalman Filtering is an effective Gauss process optimal filtering algorithm. When the object model is accurate enough and the system status and parameters are free from mutation, Kalman Filtering prediction equations and observation equations are:

$$x_k=\Phi_{k,k-1}x_{k-1}+\Gamma_{k-1}\omega_{k-1} \tag{8}$$

$$z_k=H_kx_k+m_k\ k\ge 1 \tag{9}$$

This paper assumes process noise and observation noise are Gauss white noise, satisfying:

$E\{w_k\}=0$, $E\{m_k\}=0$, $Cov(w_k,w_j)=Q_k\delta_{kj}$, $Cov(m_k,m_j)=R_k\delta_{kj}$, $Cov(w_km_j)=0$,

$$\delta_{kj}=\begin{cases}1 & k=j\\0 & k\ne j\end{cases}.$$

Initial conditions:

$$\hat{x}_0=E[x_0]=\mu_0 \tag{10}$$

$$Var\tilde{x}_0=Varx_0=P_0 \tag{11}$$

Kalman Filtering time update equations:

$$\hat{x}_{k/k-1}=\Phi_{k,k-1}\hat{x}_{k-1} \tag{12}$$

$$P_{k/k-1}=\Phi_{k,k-1}P_{k-1}\Phi_{k,k-1}^{\tau}+\Gamma_{k-1}Q_{k-1}\Gamma_{k-1}^{\tau} \tag{13}$$

Measurement updates equations:

$$\begin{cases} K_k = P_{k/k-1} H_k^{\tau} [H_k P_{k/k-1} H_k^{\tau} + R_k]^{-1} \\ \hat{x}_k = \hat{x}_{k/k-1} + K_k (z_k - H_k \hat{x}_{k/k-1}) \\ P_k = [I - K_k H_k] P_{k/k-1} \end{cases} \tag{14}$$

The 2-dimensional model of the user position is defined as follows:

$$\begin{bmatrix} x_k \\ y_k \\ v_k^x \\ v_k^y \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_{k-1} \\ y_{k-1} \\ v_{k-1}^x \\ v_{k-1}^y \end{bmatrix} + \begin{bmatrix} w_k^x \\ w_k^y \\ w_k^{vx} \\ w_k^{vy} \end{bmatrix} \tag{15}$$

$$\begin{bmatrix} z_k^x \\ z_k^y \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_k \\ y_k \\ v_k^x \\ v_k^y \end{bmatrix} + \begin{bmatrix} m_k^x \\ m_k^y \end{bmatrix} \tag{16}$$

Where x_k, y_k respectively represent moving target displacement in X direction and Y direction in the 2-dimensional plane, v_k^x and v_k^y correspond to the speed in X direction and Y direction.

5. Experiment Results and Analysis

Based on simulation scene and realistic scene, this paper compares properties of presented SK algorithm and KNN algorithm, SVR algorithm positioning accuracy root mean square error (RMSE), error percentage and cumulative distribution function (CDF) within 2 meters.

5.1. Simulation Scene

5.1.1. Establishment of the Simulation Scene

This paper first utilized the simulation environment to have a detailed performance analysis of the proposed positioning method. Positioning area was 40m*40m. 12 Access Points (AP) were distributed around. In total 1600 reference points; spacing was 1m. Based on the path, 200 test points were selected. The simulation scene is shown in Figure 1.

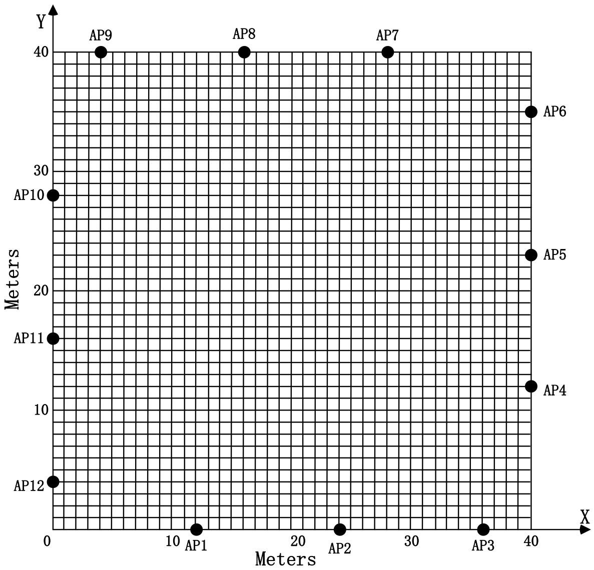

Figure 1. Simulation Scene

The following model was adopted to calculate average signal strength of each AP received at each sampling point position [20].

$$pl(d_{AP_i,p}) = pl(d_0) + 10 \cdot \alpha \cdot \log_{10}(d) \quad (17)$$

$$RSS_{AP_i,p} = Pt - pl(d_{AP_i,p}) \quad (18)$$

Where $d_{AP_i,p}$ represents the distance between access point AP_i and sampling point p, $pl(d_{AP_i,p})$ represents loss mean *of* AP_i signal at Position p from the access point, $pl(d_0)$ represents the path loss of signal transmission at reference distance d_0=1m, the signal loss, α represents path loss coefficient, Pt represents transmit power of the access point, $RSS_{AP_i,p}$ represents the average signal strength received at the sampling point position p from No. I access point. The basic parameters are shown in Table 1:

Table 1. Parameters Values

Parameter	Value
$Pl(d_0)$	41.5dBm
α	2
Pt	15dBm

In order to imitate the real environment, in experiments, the average signal strength received at each test point was added with Gauss noise with the mean μ=0 and variance σ=1.

5.1.2. Experimental Results

As can be seen from Figure 2, SVR algorithm RMSE is significantly better than KNN algorithm, SK algorithm RMSE outweighs SVR, and with the increasing of the number of test points, KNN algorithm RMSE stabilizes at around 1.59m, SVR algorithm RMSE stabilizes at around 1.42m, SK algorithm RMSE stabilizes at about 1.26m, respectively lower than SVR and KNN algorithm RMSE by about 10% and 17%.

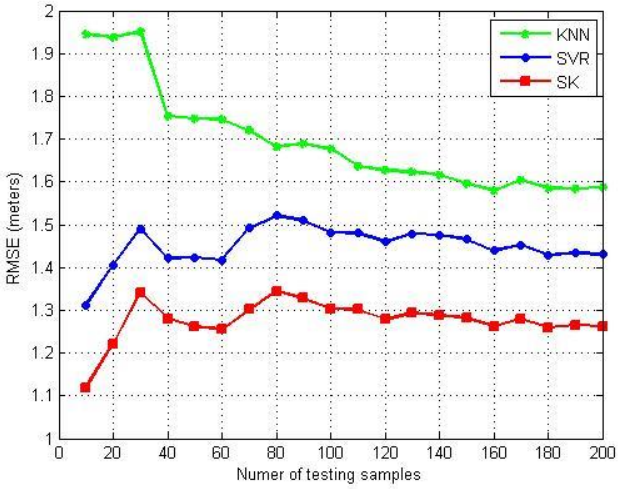

Figure 2. Comparison of RMSE

Figure 3 shows in terms of 2m positioning error confidence probability, SVR positioning algorithm outweighs KNN in properties, SK positioning outweighs SVR in properties. In case of 200 test points, KNN confidence probability was 78%, SVR confidence probability was 88%. The latter outweighed the former by 10%. SK confidence probability was 94%, outweighing SVR by 6%. Overall, with the increase in the number of test points, each algorithm confidence probability is stable.

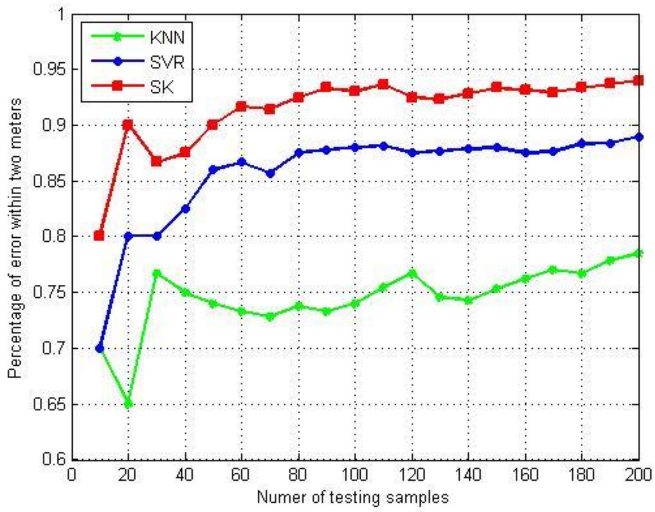

Figure 3. Comparison of Percentage of Error within 2 Meters

As can be seen from Figure 4, in case of the error distance within 3 meter, SK outweighs KNN and SVR in confidence probability. In addition, in case the positioning error with a confidence probability within 80% is considered as the indicator of positioning accuracy, SK algorithm can improve the positioning accuracy within 80% from KNN algorithm 2 meters to 1.5 meters, improving positioning properties by 25%.

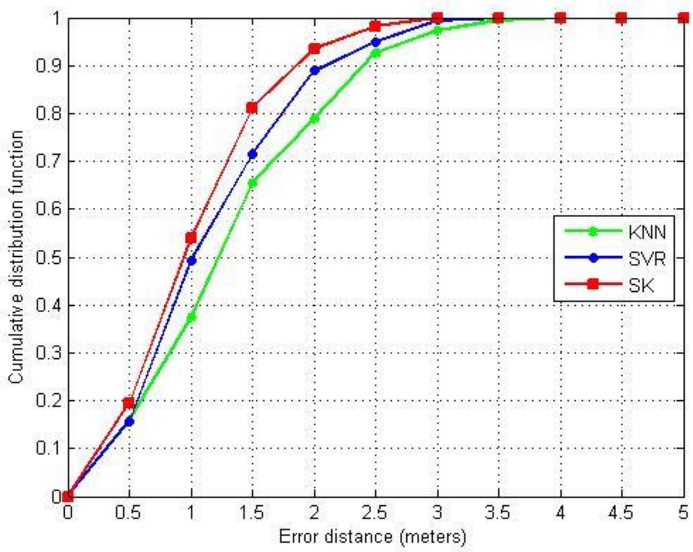

Figure 4. Comparison of CDF

5.2 Realistic Scene

5.2.1. Establishment of the Realistic Scene

This paper's indoor positioning experimental environment is Floor 4 of a lab building, with a length of 50 meter, a width of 20 meters, and 13 AP, a distance between AP of about 20 meters. Test area includes the corridor and halls on its sides. Experimental site sampling path is shown in Figure 5. The dots in the figure represent reference points, squares represent test points, and arrows represent the path and direction.

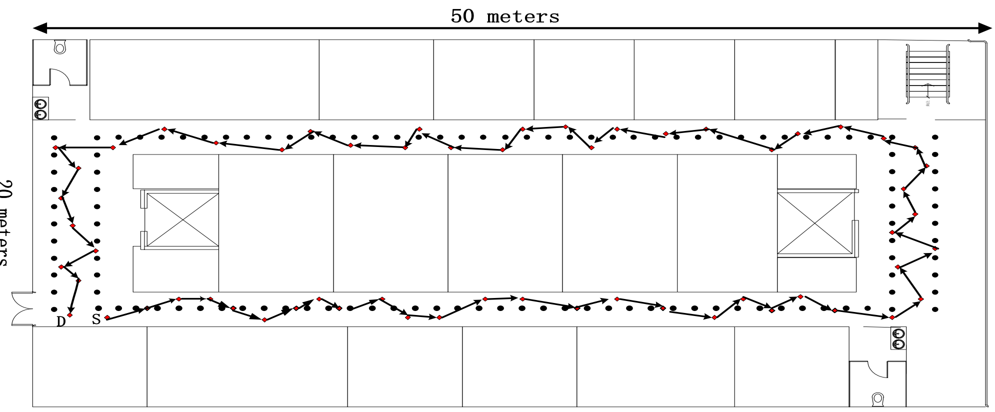

Figure 5. Realistic Scene

In the offline phase, 116 reference points were adopted, the spacing between the reference points was 1 meter, the sampling time of each reference point was 180 seconds, that is, each reference point reading signal strength was 180 times (terminal signal strength scanning frequency was once/s). In the online real-time follow-up phase, 60 test points were adopted, each test point sampling time was 30 seconds, that is, each test point reading signal strength was 30 times.

5.2.2. Experimental Results

Figure 6 shows that with the increase in the number of test points, each algorithm RMSE stabilized, SK outweighed KNN and SVR algorithm in properties, SVR slightly outweighed KNN in properties. In case of 60 test points, SK was lower than KNN and SVR in RMSE by 28% and 16% respectively.

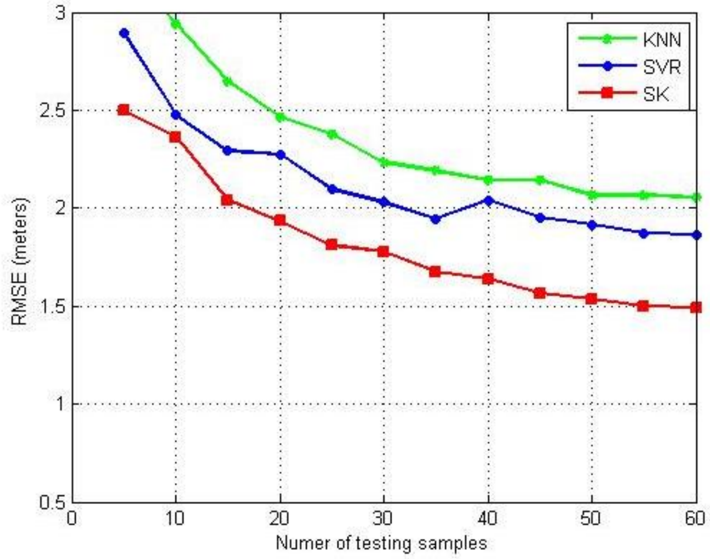

Figure 6. Comparison of RMSE

Figure 7 shows the changes in positioning error confidence probability of each algorithm within 2 meters with increasing of the number of test points. SVR algorithm evidently outweighed KNN in confidence probability. SK algorithm significantly outweighed SVR algorithm in confidence probability. In case of 60 test points, SK outweighed KNN in confidence probability by 24%. In terms of environment simulation results, the overall confidence probability decreased, indicating the positioning results with the positioning error greater than 2 meters increased with the increase of the number of test points against the realistic environment.

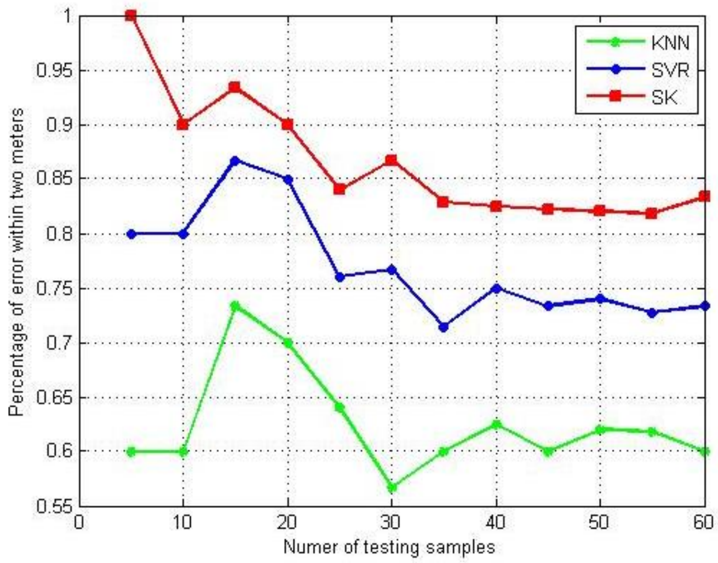

Figure 7. Comparison of Percentage of Error within 2 Meters

Figure 8 shows the confidence probability of each algorithm against different positioning error distances. SK outweighed the other two algorithms. SVR overall outweighed KNN in properties slightly, especially in case the positioning error was greater than 2 meters. Compared with Figure 4, the properties of all algorithms were the same.

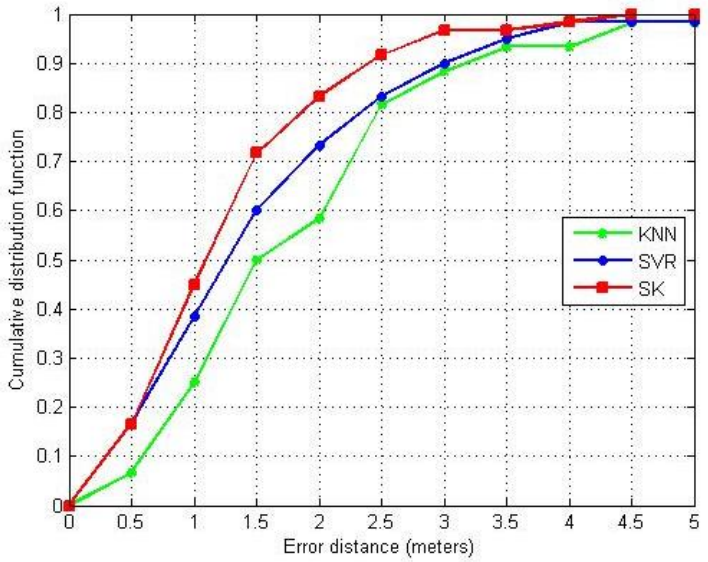

Figure 8. Comparison of CDF

Figure 9 shows changes in X coordinate after SVR positioning results were processed with Kalman Filtering. As can be seen from the figure, filtering can significantly correct SVR positioning results, making it imitate the real X coordinate, reducing the error, which shows Kalman algorithm can balance the positioning results, making the user's position mobile regular.

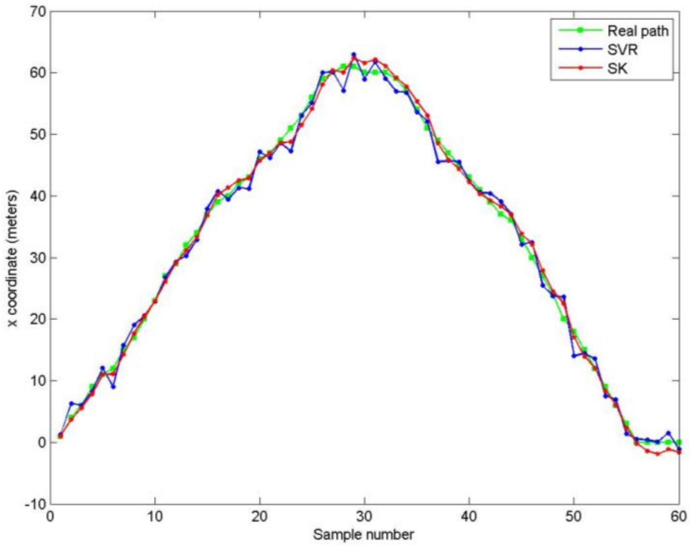

Figure 9. Kalman Filtering Simulator of x Coordinate

6. Conclusion and Future Work

This paper adopted SVR to achieve the indoor positioning, conducted training with the data obtained through signal filtering in the offline phase so as to obtain the position prediction model, which was utilized to estimate the position coordinates of the moving target in the online phase. In order to make the user's position regular, Kalman Filtering was taken to filter and correct SVR positioning results, and the properties of the algorithm was verified against the simulation environment and realistic environment. Experimental results show that the positioning accuracy and stability of the system were improved. This experiment was characterized by fewer reference points and test points of the realistic scene, and narrow sampling space, which affected the properties of the SVR algorithm to a certain extent. It is planned to extend this experiment in the future, collecting more test points in multiple subspaces. It is also planned to try to utilize the extended Kalman Filtering and particle filtering algorithm to process the estimated user's position so as to verify whether the system's positioning properties are improved.

Acknowledgements

This work is support by Shanghai Municipal Bureau of Quality and Technology Supervision of China (no. 2014QK140), the National Natural Science Foundation of China (no. 61372086), and the Foundation of Science and Technology Commission of Shanghai (no. 13511500300).

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