Precise Transceiver-Free Localization in Complex Indoor Environment

Rui Mao, Peng Xiang, Dian Zhang

College of Computer Science and Software, Shenzhen University, Shenzhen 518060, China

Abstract: Transceiver-free object localization can localize target through using Radio Frequency (RF) technologies without carrying any device, which attracts many researchers' attentions. Most traditional technologies usually first deploy a number of reference nodes which are able to communicate with each other, then select only some wireless links, whose signals are affected the most by the transceiver-free target, to estimate the target position. However, such traditional technologies adopt an ideal model for the target, the other link information and environment interference behavior are not considered comprehensively. In order to overcome this drawback, we propose a method which is able to precisely estimate the transceiver-free target position. It not only can leverage more link information, but also take environmental interference into account. Two algorithms are proposed in our system, one is Best K-Nearest Neighbor (KNN) algorithm, the other is Support Vector Regression (SVR) algorithm. Our experiments are based on TelosB sensor nodes and performed in different complex lab areas which have many different furniture and equipment. The experiment results show that the average localization error is round 1.1*m*. Compared with traditional methods, the localization accuracy is increased nearly two times.

Keywords: indoor localization; transceiver-free; radio map; support vector regression

I. INTRODUCTION

Transceiver-free object localization is very important for many emerging location-based services, e.g., health sensing technologies [21][22], safe guard systems, which attracts many researchers' attentions [1][16][19]. In the ambient assisted living (AAL) systems, the elderly people can be located and monitored by using these technologies without carrying any radio device. Among various transceiver-free object localization technologies, Radio Frequency (RF)-based approaches are the most promising and popular [2][3][11][14] because of their low-cost and easy availability for almost all the common wireless devices. In traditional transceiver-free object localization technologies, usually a large number of reference nodes will be deployed in advance. Each reference nodes will act as both transmitter and receiver. When the target enters this environment, it will cause the signal of some wireless links to change, then they can utilize this change information plus the corresponding location information to localize the target. Thus, only some wireless links, whose signals are affected the most by the transceiver-free target, are selected to estimate the target position. However, such traditional technologies adopt only an ideal model for the target, the other link information and environment interference behavior are not considered comprehensively. For example, radio signals are easily reflected, refracted, and scattered by indoor objects, which can affect the accuracy of indoor localization.

In order to overcome the drawback above, we propose a method, which is able to precisely calculate the transceiver-free target position. It not only can leverage more link information, but also take environmental interference into account. The basic idea of this paper is to utilize all the wireless link information to construct a comprehensive radio map, then we can localize the target by referring to such map. In the meanwhile, we propose two localization algorithms: K-Nearest Neighbor (KNN) algorithm and Support Vector Regression (SVR) algorithm. The Former one is easy to implement, while the latter one is able to utilize all the wireless link information to precisely localize the target.

Our experiments are performed at two different complex lab areas which have many different furniture and equipment. The size of each lab area is also different. Through using our algorithms, the average error of localization accuracy can reach 1.1*m*. Compared with the traditional RSSI-based approaches, the accuracy is improved by 2 times. Furthermore, the latency of real-time tracking is only about 70*ms*.

The remaining of this paper is organized as follows: in the next section, we will provide some related work. Section 3 will introduce our methodology to localize the target object. The experimental results and evaluation of our method will be shown in section 4. At last, we will conclude this paper and point out our future work in section 5.

II. Related Work

There are a large number of indoor localization technologies for transceiver-free object. In general, they can be classified into two categories, non-radio based technologies and radio based technologies. What's more, many device-free object localizations based on received signal strength indicator (RSSI). Different from RSSI, CSI is a fine-grained value from the Physical layer which describes the amplitude and phase [31] and can achieve a great positioning accuracy, however, in order to get the CSI information, we need some additional custom hardware. While the RSSI information can be easily obtained, so we use the RSSI for localization in our system.

Non-radio based technologies are listed mainly in the following.

Infrared [5] utilizes the indoor optical sensor emitting a lot of infrared rays. If the transceiver-free target blocks some rays, such information can be used for localization. However, infrared rays cannot pass through the barrier. Moreover, this technology requires dense deployment and high cost. Thus, the infrared technology is just suitable for short-distance transmission and apt to be affected by light in the room. So this technology has an inevitable limitation in the precise indoor localization.

Video [4][10] can localize the transceiver-free target by using various video-based algorithms for image processing. Although their localization accuracy is high, such technologies still have the following drawbacks. First, they are limited in the dark area. Second, the cameras around should be careful deployed to avoid some area not be covered. Especially for some complex environment, it is difficult for the cameras to cover the whole spaces. At last, the privacy of people cannot be protected for video technologies.

Ultrasound [6] can be used for device-free localization by emitting an ultrasonic pulse. This technology can reach a higher positioning accuracy, but multipath propagation effect and non-line propagation have a great impact on ultrasound. What's more, it requires a lot of underlying hardware infrastructure investment and the cost is too high. Furthermore, the coverage area for the ultrasonic sensors are limited, result in dense deployment in the real application.

Radio based technology [1][2][3][23] uses Radio Frequency (RF) for non-contact two-way communication to do data exchange, and then achieve the purpose of targeting. This technique can be applied to short-distance, generally up to tens of meters. But it can reach a centimeter-level positioning accuracy in a few milliseconds with large transmission range and low cost. Therefore, RF-based localization is very popular and promising [13].

In theory, there are three traditional RF-based models: Free Space Propagation Model [27], Log-Distance Path Loss Model [24] and Hata Model [33].

The Free Space Propagation Model requires no obstacle environment, making it difficult in real scenario. The argument of Log-Distance Path Loss Model is difficult to determine, which can make a big impact on localization accuracy; Hata Model cannot be used in the indoor environment. All the previous models cannot be directly applied in the transceiver-free object localization, due to its requirement on the target to carry a transmitter or a receiver, or both.

The recent transceiver-free object localization usually adopts an ideal model [25]. Under an infrastructure of a number of reference nodes which are able to communicate to each other, they supposed the transceiver-free target usually will cause the signals of those wireless links nearby to change a lot. A signal dynamic property is proposed accordingly. They do not consider too much about the environmental and other interference to the signal changes. Sometime, such interference will also cause the signals of other wireless links to change. Therefore, the localization accuracy will decrease especially in real complex indoor environments. Our proposed algorithms in this paper consider all the signal information among wireless link, and can obtain more accurate localization result.

On the other hand, radio based technologies in general include Wi-Fi, Wireless Sensor Network, RFID and Bluetooth.

Wi-Fi [7][9][15] is a very popular platform, which can implement the wide range of positioning, monitoring and tracking in many application areas. Among the various Wi-Fi localization technologies, WiFi technologies is very popular, which utilizes the signal strength information to locate the object. Generally, this technology can achieve a high accuracy and have a wide applicability.

Wireless Sensor Network [23] is an emerging short-range, low-rate wireless network technology [17][18], which localize the target through the signal strength information among each sensors. What's more, the most notable features of WSN are low power consumption and low cost.

Radio Frequency Identification (RFID) [2][5][29][30] technology utilizes the radio frequency mode to transfer data, for the purposes of automatically tracking tags attached to objects. This technique can be effective in a short-distance, generally up to tens of meters. But it is able to achieve a centimeter-level indoor positioning accuracy in a few milliseconds with a large transmission range and low cost. Because of its non-contact and non-line of sight, it is becoming to be the popular indoor positioning technology.

Bluetooth [8][12][15] can be used for positioning by measuring the signal strength. The advantage of Bluetooth technology is that it is small and easy to integrate in mobile phone, which makes it widely applied. However, its drawback is that the price of Bluetooth devices is at high cost, and the stability of the Bluetooth system is easy affected in the complex environment.

Besides, there are also many device-based object localization technologies that can achieve great positioning effect. For example, the system of Graph Model Based Indoor Tracking [29], which builds an RFID specific reader deployment graph model that is then used to construct and refine trajectories. What's more, the two R-tree based structures [30] based on RFID were proposed for indexing the trajectories of moving objects, which can be efficiently and robustly applied for a wide range.

III. METHODOLOGY

In this section, we will introduce the main idea of our method at first. In the following, the two algorithms used to track the target will be proposed in detail: K-Nearest Neighbor algorithm (KNN) and Support Vector Regression algorithm (SVR).

3.1 The Basic Idea

In this subsection, we will show the way how to localize the target. We carry out our experiment based on a number of reference nodes on the ceiling indoors (here, each node act as both transmitter and receiver). Suppose there are n number of reference nodes, there are corresponding $m = C_n^2$ number of wireless links (we treat the symmetric links as one link). The signals of the communication links between the sensors can be interfered when the target appears in this environment. Our basic idea is first to construct a radio map in the offline phase. For each target positions on the ground (here we arrange a human to act as the target and ground area is assumed to be able to be described by a two-dimensional coordinate), we collect the Received Signal Strength of each wireless link, and apply a Min-Max normalization to these vector values

$$x^* = \frac{x - \min}{\max - \min}$$

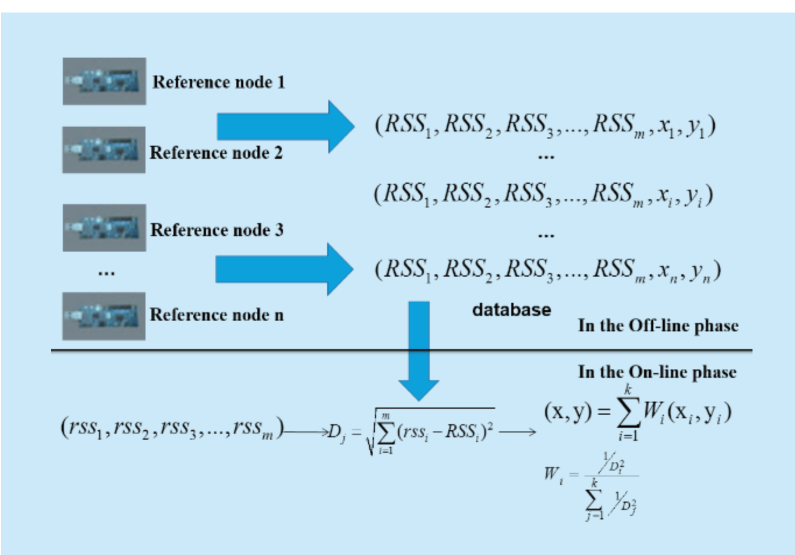

Fig.1 *KNN system diagram*

where x^* is the normalized value of x, min is the minimum value for the sample data, max is the maximum value for the sample data.

Therefore, we may eliminate the variance among different devices. For each target position on the ground, we will have a vector whose dimension is $m = C_n^2$.

Later in the online tracking phase, we may use the K-Nearest Neighbor algorithm (KNN) and Support Vector Regression algorithm (SVR) algorithm in the localization. Since the target may cause the signals of some wireless links to change, the KNN algorithm aims to choose those human positions on the ground in the radio map, whose RSS information of the whole wireless links is most similar, in localization. While for the SVR algorithm, we intend to simulate the relation (function) between the RSS information for all the wireless links and the target location in the offline phase, such relation (function) is then used in the online tracking.

The details for each algorithm are shown in the next subsections.

3.2 K-nearest neighbor algorithm

In the previous subsection, we have already shown how to build the radio map in the offline phase. As described Figure 1, the upper part above the line shows the offline phase. Suppose in total we have n number of reference nodes on the ceiling. Each node is both transmitter and receiver. Since we regards the symmetric links as one link, we have $m = C_n^2$ number of links. For each human place on the ground, we collect the *RSS* information of each wireless link. Suppose we have h number of test human places on the ground in the offline phase, for each place we may collect m RSS values, and each one is corresponding to one wireless link. We use a vector $B_j = (rss_{j1}, rss_{j2}, \ldots, rss_{jm})$ to represent this value, where $j \in (1, h)$.

In the online phase, as shown in the bottom part below the line in Figure 1, when the target enters the environment, we also may get the RSS information for each wireless link, although the signals of some wireless links will be interfered by the target. Here, we use a vector $A = (RSS_1, RSS_2, ..., RSS_m)$ to represent this information. We aim to find those human places on the ground in the offline radio map, whose RSS vectors are most similar to the RSS vector by the target. Therefore, for each human place j on the ground, we are able to calculate its Euclidean distance D_j to the target vector as follows

$$D_j = \sqrt{\sum_{i=1}^{m} (RSS_i - rss_{ji})^2}$$

Here, $j \in (1, h)$, and again h is number of test human places on the ground in the offline phase. After calculating h number of these Euclidean distances, we choose the k places where the Euclidean distance is the smallest. Then, we can calculate the coordinate of target as follows

$$(x, y) = \sum_{i=1}^{k} W_i(x_i, y_i)$$

where (x_i, y_i) is the coordinate of the chosen known place in the radio map, W_i is the weight value of the i-th nearest neighboring, which is able to be calculated as follows

$$W_i = \frac{1/D_i^2}{\sum_{l=1}^{k} 1/D_l^2}$$

3.3 Support vector regression (SVR) algorithm

In this subsection, we will show that how to calculate the coordinate of target by using SVR algorithm in detail.

As Figure 2 shows, the SVR forecasting can be formalized to find a function $f(k)$ between the training samples and the target location. The training sample in the offline phase is $K = \{(k_i, O_i), i=1,...,h\}$, where $k_i \in R^m$ is the i-th RSSI information vector for i-th training sample whose vector dimension is m. $O_i \in R^2$ is the target location on the ground for i-th training sample and h is the number of samples. Since we only consider the target location on the ground, the vector dimension for O_i is 2. Training a SVR forecasting model is to find a function with a form like

$$f(k) = \sum_{i=1}^{h} (\alpha_i - \alpha_i^*) y(k_i, k) + b$$

where $y(k_i, k)$ is the kernel function, $\alpha = (\alpha_1, \ldots, \alpha_h)^T$, $\alpha^* = (\alpha_1^*, \ldots, \alpha_h^*)^T$ and b are the parameters of the model. In order to find α_i, α_i^*, i=1,...,h, we need to solve the optimization problem as follows

$$\min\{\frac{1}{2}\sum_{i,j=1}^{h} (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) y(x_i, x_j) + \sum_{i=1}^{h} (\alpha_i + \alpha_i^*)\varepsilon - \sum_{i=1}^{h} (\alpha_i - \alpha_i^*) x_i\}$$

in condition that:

$$\sum_{i=1}^{h} (\alpha_i - \alpha_i^*) = 0, 0 \leqslant \alpha_i, \alpha_i^* \leqslant C$$

where ε and C are the constants greater than zero, h is the number of training sample.

Here, for the kernel function, we adopt the RBF kernel function [27], which is the most widely used

$$y(k_i, k) = exp(-\frac{\|k_i - k\|^2}{\sigma^2})$$

where $\sigma > 0$ is the width of the kernel.

By using the standard library LIBSVM [26], we can train an SVR model in the offline phase. In the online phase, when the target appears in the environment, a new RSSI information vector for the whole wireless links will be received. We are able to predict the target location on the ground through using this function.

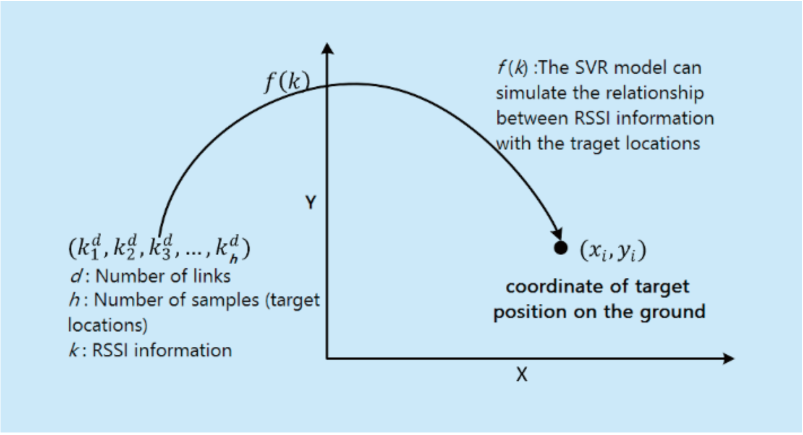

Fig.2 *Basic idea of SVR*

IV. EXPERIMENTATION AND EVALUATION

In this section, we will introduce the implement and architecture of our system and then show the performance evaluation.

4.1 System implementation

We perform the experiments in two different environments: *Environment A* is a $10\times9m^2$ laboratory with 15 nodes placed on the ceiling as Figure 4 shown; *Environment B* is a $9\times8m^2$ laboratory with 12 nodes deployed on the ceiling as shown in Figure 5. Our system is based on TelosB sensor node [20], which integrates the CC2420 radio chip and MSP430 micro-controller [32]. In the process of communication, the transmission power is fixed at -10*dBm* and the channel is defaulted at 11. Each sensor nodes on the ceiling are both transmitter and receiver.

Since the sensors can communicate with each other, we get the RSSI information to build a radio map. Later in the online phase, when the target enters the environment, the new RSSI information is transmitted back to sink Based on the radio map, our system use the proposed algorithms to calculate the location of the target.

4.2 System architecture

As Figure 3 shows our localization system architecture, our localization system runs in 2 steps. First, we build a database to store the training data, and training data consists of the values of Received Signal Strength among reference nodes, and location information which is known before the experiment. We have collected 153 data for training in Environment A and 135 training data in Environment B.

Later, in the online phase, the RSS information is also collected and transmitted to the sink. Then use the proposed algorithms to localize the transceiver-free object. The KNN algorithm will calculate the Euclidean distances between the received RSS information with the RSS data stored in the database, then calculate the target coordinates based on the *k* smallest Euclidean distances. On the other hand, SVR algorithm needs to process the data at first to find the optimal parameters of the test data, then getting the training model. Through using the training model, we get the coordinate of unknown object.

4.3 Comparison of different localization algorithms

In this subsection, we compare the two algorithms of our system with traditional midpoint location algorithm [1].

In our system, we set k=3 for KNN algorithm as empirically setting. Figure 6 and Figure 7 show the Cumulative Density of Function (CDF) in absolute errors. We show that in different Environments, the localization accuracy of our KNN and SVR algorithms is better than the traditional midpoint location algorithm. We may also see that, SVR algo-

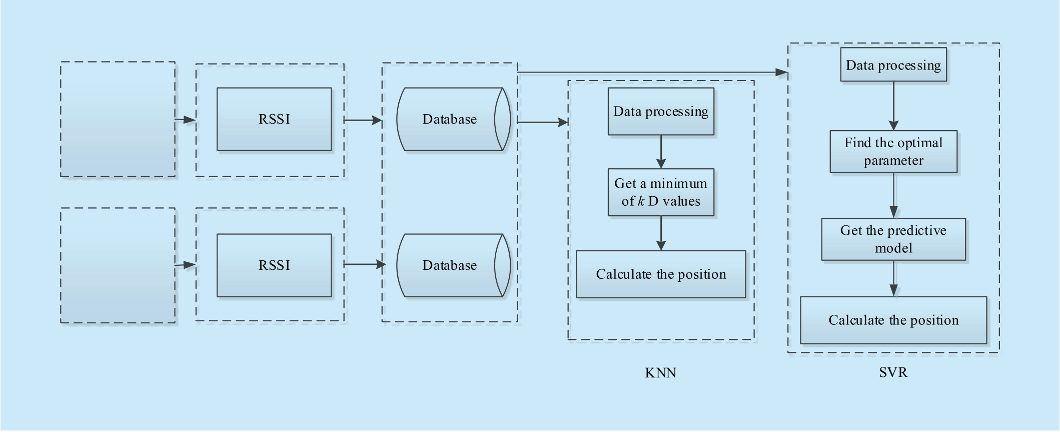

Fig.3 *Architecture of transceiver-free object localization*

rithm also outperforms the KNN algorithm. In Environment A, as the Figure 6 shown, the averaged localization error of SVR is 1.5*m* while KNN is 1.9*m*, the traditional midpoint algorithm is only 2.7*m,* the accuracy is improved by two times. In Environment B, the Figure 7 shows that the averaged localization accuracy of SVR is 1.1*m* while the KNN is 2.1*m*, the traditional midpoint algorithm is 2.6*m* in the Environment B, and the accuracy is improved by nearly three times.

We find that, no matter which environment is selected, the SVR algorithm always is the best. So in our later experiment, we use the SVR algorithm in localization.

4.4 The impact of different environment

In this subsection, we will introduce the impact of different environment on localization accuracy. Environment A contains more barriers, furniture and devices than Environment B.

We find that, in the environment A, when using the SVR and KNN algorithm to track the target, the localization accuracy is 1.5*m* and 1.9*m,* respectively. The accuracy using traditional midpoint location algorithm is only 2.7*m*. However, in the Environment B, the localization accuracy of our system using SVR and KNN algorithm are 1.1*m* and 2.1*m* respectively. When using traditional midpoint location algorithm, the average error of tracking is 2.6*m*.

We may observe that, the localization accuracy of our system in the Environment B is better than in the Environment A. The reason is that Environment A is much more complex, and the stuff inside cause many multipath signals among the commutations of the reference nodes, which will reduce the localization accuracy. However, we also find that, no matter in which kind of environments, SVR algorithm always shows higher localization accuracy.

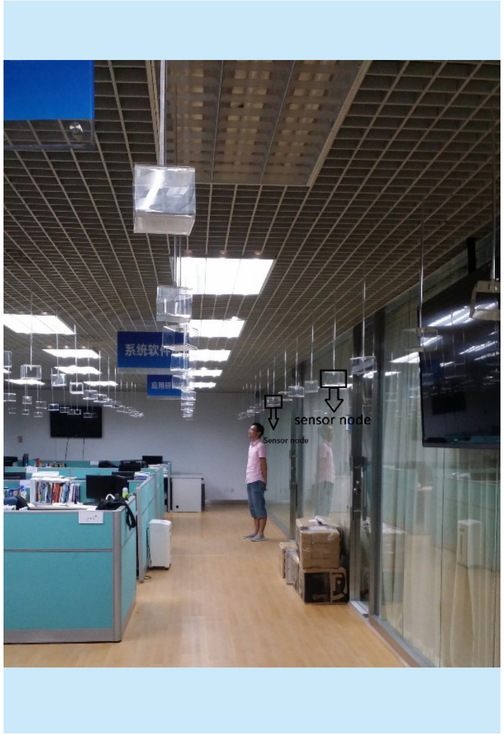

Fig.4 *Environment A*

Fig.5 *Environment B*

4.5 Localization accuracy

In the last subsection, we have shown that our method can achieve a higher localization accuracy. Thus, in this subsection, we will show the localization result of our method using SVR algorithm. In order to reach a high accuracy, we performed this experiment by

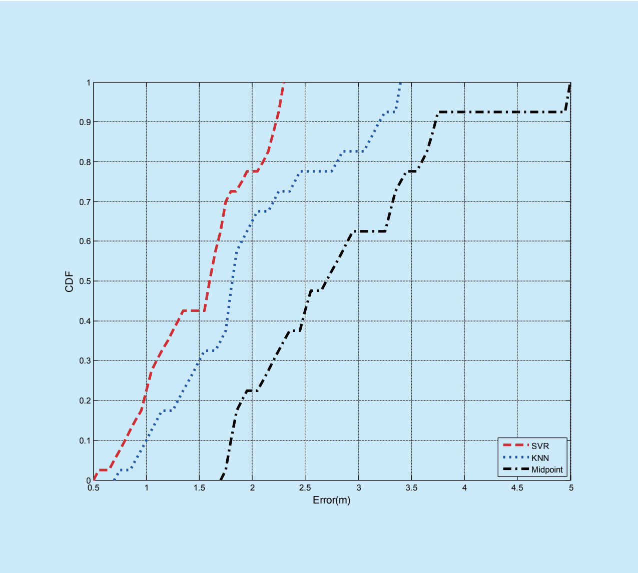

Fig.6 *Algorithm Comparison in Environment A*

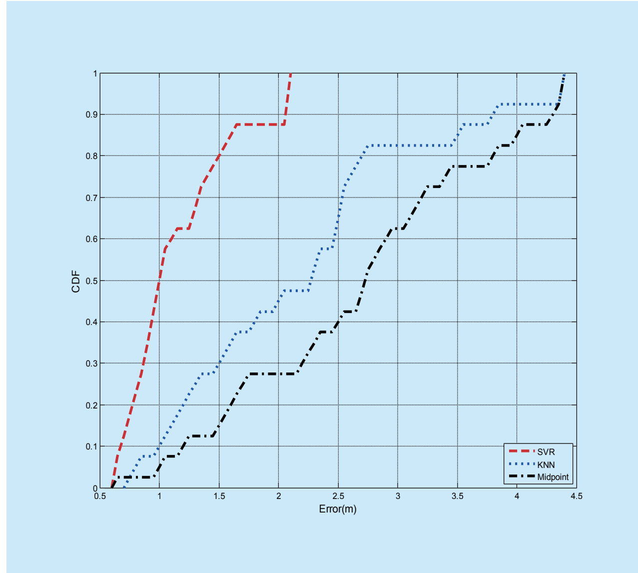

Fig.7 *Algorithm Comparison in Environment B*

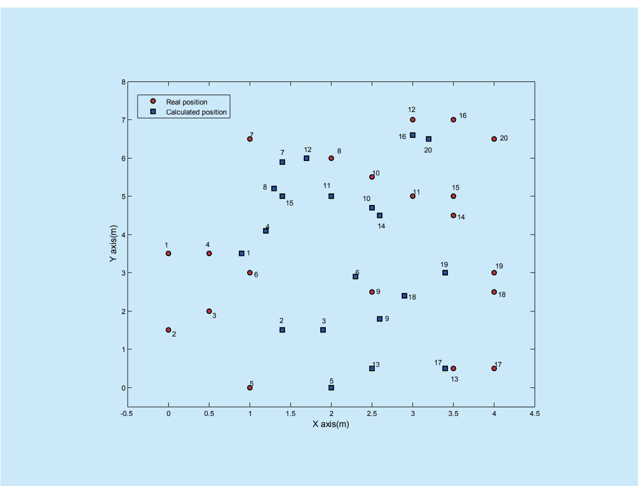

Fig.8 *Localization result*

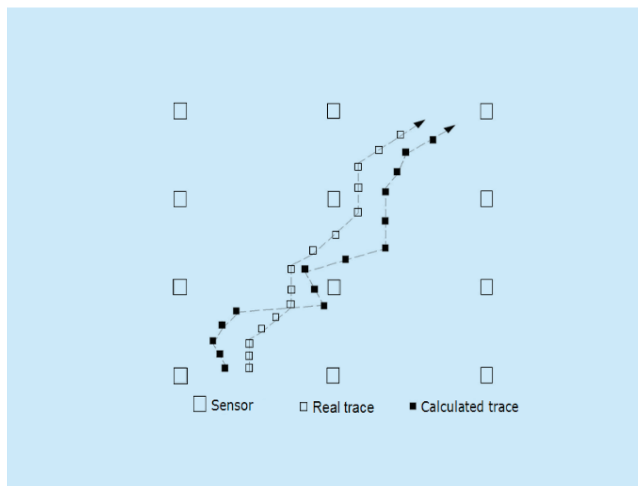

Fig.9 *The Localization of the moving target*

using 12 sensor nodes which are deployed on the ceiling. The distance from one sensor to another sensor is 2*m* [14]. In the experiment, we have collected twenty samples, and the result of localization is shown in Figure 8, the red circle with numbers is the real position of tracking node while the blue square with numbers is the calculated position. We can find that by using our SVR algorithm, the localization accuracy can reach 1.1*m*. Compared with traditional methods, the localization accuracy is increased nearly two times.

4.6 Moving target

In this subsection, we will show the result of our method to track the moving target. In the Environment B, we arrange a person walk through a fixed trace and the speed of the person moving is around 0.5*m/s*. We have done 10 different rounds of test. One of the tracking results is shown in Figure 9. The 12 big squares are the reference nodes. The dash line of big squares is the real trace of target, while the dash line of black squares is the calculated trace by using our SVR method. The average tracking error of the moving target can reach 1.3*m*.

4.7 Latency

In this subsection, we will discuss the latency of our system, which mainly depends on the beacon interval of each node. The study [28] shows that one TelosB sensor node takes an average of 7*ms* to transmit a packet with 51 bytes. Since we deployed a number reference sensor nodes, in order to avoid collision, we increase the sensor' interval as 14*ms* to transmit one packet. In our system, for each wireless link, we collect five packets in average, so the latency is 5×14*ms*=70*ms*.

V. Conclusion and Future Work

In this paper, we have proposed a new method that is able to precisely calculate the transceiver-free object position. Our method is able to leverage more communication link information and take the environmental interference into account to track the target. In our system, we introduced two algorithms, one is Best K-Nearest Neighbor (KNN) algorithm, and the other is Support Vector Regression (SVR) algorithm. Besides, our experiments are performed at two different complex lab areas. Through this method, the average error of localization accuracy can reach 1.1*m*, its accuracy has improved more than 2 times compared with the traditional methods.

As future work, first, we will try our method in a larger indoor area. Furthermore, it is our first try to track the single transceiver-free target, in the future, we will try to localize two or more objects by using our method. At last, since our experiments are conducted in a 2*D* area, we will try to deploy our system in a 3D area for a better real-time performance.

Acknowledgement

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Biographies

Rui Mao, received his B.S. (1997) and M.S. (2000) in computer science from the University of Science and Technology of China, and another M.S. (2006) in statistics and his Ph.D. (2007) in computer science from the University of Texas at Austin. After three years at Oracle USA Corporation, he joined Shenzhen University in 2010, where he is now an associate professor in the College of Computer Science and Software Engineering. His research interests include universal data management and analysis, and high-performance computing. Email: mao@szu.edu.cn

Dian Zhang, the corresponding author, received the PhD degree in computer science and engineering from the Hong Kong university of Science and Technology, Hong Kong, in 2010. She is now an associate professor in the College of Computer Science and Software, Shenzhen University. Her research interests include wireless sensor networks, pervasive computing and Networking and Distributed Systems. Email: zhangd@szu.edu.cn

Peng Xiang, he is currently studying for his M.S. degree in College of Computer Science and Software, Shenzhen University, China. His research interests focus on wireless sensor networks. Email: xiangpeng 90812@gmail.com