A multivariate analysis-based for range-free localization algorithm

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Abstract

Proposed an improved DV-Hop localization algorithm (PLS-DVHop) based on partial least squares, which uses the partial least squares to model of hop-count and the Euclidean distances, along with the maximum covariance of input matrix and output matrix to estimate the location of unknown nodes. PLS-DVHop has strong adaptability for different deployment network, and overcomes the shortage of only suitable for isotropic networks in the original algorithm. Simulation results show that PLS-DVHop algorithm has high estimate precision and stable performance, can adapt to different network topologies, and is very suitable for large scale deployment network.

Keywords: range-free localization, wireless sensor network, partial least squares

1 Introduction

Wireless sensor network (WSN) [1, 2] is constituted in ways of self-organization and multi-hop by large volumes of sensor nodes with communication and computation capability. Nodes in the network are able to collaboratively perceive, collect, process, and transmit the information of perceived objects within the coverage area of the network, as well as to report the information to users. WSN has great potential application value in military, transportation, medical care, and environment monitoring [1]. Location estimation is a key issue for WSN [3, 4]. Different from traditional networks, WSN is a data-based network. Thus, in WSN localization researches, statistics and multivariate analysis methods are often applied for quantitative analysis.

In the application of WSN, nodes' location information can be acquired by adding global position system (GPS)/BeiDou Navigation Satellite System (BDS) devices on nodes. However, this way is only applicable with outdoor. Besides, GPS/BDS device is large in volume, and high in cost and energy consumption. Moreover, GPS/BDS device also needs stable base installations. These facts have made it difficult to realize the requirements of WSN, which is "low price, low cost and low energy consumption" [5]. As for this, in practice, only some of the nodes can be installed with GPS/BDS device. For the rest nodes, their location information can only be estimated via a certain algorithm or method. After several years' development, researchers have proposed many node localization approaches. According to whether the range information is used among the localization process, the localization techniques can be classified into range-based and range-free [3, 4, 6]. The range-based method exploits distance or angle information between neighbour nodes, and then uses the information to localize nodes. The range-based localization has higher location accuracy but requires additional hardware support and thus, is very expensive to be used in large scale sensor network. The range-free localization is being considered as a cost-effective alternative to range-based methods because of hardware limitation in large scale deployment. On the other hand, range-free schemes do not need additional hardware support and makes use of connectivity, multi-hop routing and other information between nodes to estimate nodes location. Therefore, range-free technique is considered to be most effective solution for the localization issues in WSN.

The DV-Hop localization algorithm proposed by Dragos Niculescuet et al. [7, 8] from Rutgers University is one of a series of distributed localization algorithms, it is a localization algorithm not related to the distance, it smartly uses the distance vector routing and the idea of GPS localization, and this algorithm has great distributive and expandability. DV-Hop method is an ideology based on distance vector routing and GPS, which makes use of hop distance to replace real distance between nodes. Eventually, least squares are applied to estimate the position. DV-hop algorithm assumes that the network is isotropic and uniformly distributed, that is, when the properties of the graph are the same in all directions, so that the corrections that are deployed reasonably estimate the distances between hops. Unfortunately, in practice, networks may be anisotropic and may contain com plex inner or outer boundaries, which make the least hop counts deviating the Euclidean distances. This paper integrates PLS in multivariate analysis, making use of the correlation between hop-counts and Euclidean distances between known nodes to establish an optimal linear conversion matrix. On this basis, the matrix is used to convert hop-

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counts between unknown nodes and known nodes into distance, so as to realize compensation on distance estimation in networks with unevenly distributed nodes, reaching the effect of high localization accuracy.

2 Related works

In recent years, it has become a new research hot spot to make use of multivariate analysis technique in modelling and algorithm design of localization mechanism [9, 10]. The method puts to use the relation between distribution feature and measurement information of known nodes to establish a mapping function. On this basis, the function will be used to estimate the location of unknown nodes. Compared with previous methods, multivariate analysis is able to effectively discover network topology, correlation and other information hidden behind data. Lim et al. [11] proposed a PDM (Proximity Distance Map) algorithm based on TSVD (Truncated Singular Value Decomposition) technique. PDM describes the optimal linear transformations between the hop-count and the Euclidean distances under the least-squares metric. With the help of PDM, an unknown node is able to obtain more accurate distance translation, thus to get a better location estimation. Firstly, the PDM method uses matrices to express the collected Euclidean distances and the hop-count between known nodes; secondly, TSVD technique is used to conduct linear transformation of two matrices to obtain an optimum linear transformation model; lastly, the hop-counts from the unknown nodes to the known nodes will be applied to this model to estimate the Euclidean distances between the unknown nodes and the known node. In essence, TSVD [12] is a multivariable linear regularization learning method, the estimated Euclidean distances obtained through method is actually the weighted sum of the estimated values of other known nodes in the monitoring area, and therefore, the obtained estimated value is close to the actual value. In addition, the TSVD method has abandoned the small singular values, which can to a certain extent reduce the impact of noise during the transformation process, so the collinearity problem during the localization process can be avoided, and the stability of algorithm can be increased. All these have caused the algorithm to have a low requirement for the deployment of sensor nodes, connection and signal attenuation method, which more benefits its use in complex application environments. In a certain degree, TSVD can solve some problems of range-free method, but the literature and experiment show that the PDM method only works under certain conditions, and when the beacon nodes are sparse or various radio ranges have serious anisotropy, the performance of TSVD method will sharply decrease. The main drawback of PDM is that it need to set a threshold parameter k. TSVD technique directly sets the singular values smaller than the threshold parameter k as zero, and if k is properly chosen, the solution of TSVD is stable, otherwise, it will reduce the algorithm's performance. Moreover, the PDM method has not conducted standard processing to the hop-counts and Euclidean distances, and different dimensions have caused a certain degree of data submergence. In addition, TSVD modelling only takes into consideration hop-counts information, disregarding Euclidean distance information. As for this, the model built is unable to truly reflect the relationship between hop-counts and real distance. Inspired by PDM method, Lee et al. [13, 14] put forward SVR-based localization method – LSVR (Localization through Support Vector Regression). The localization method is fit for different networking environment. Moreover, under small sample condition, it still leads to good positioning accuracy. However, LSVR is a multi-input and single-output algorithm [15]. In practical localization practices, modelling is to be performed frequently, sharply increasing the complexity of the algorithm. Moreover, with the number of beacons increases, time and space resource required by positioning will grow geometrically.

In order to reduce the complexity of localization problem, to improve the generalization performance of positioning method, and to simplify localization model, it is quite necessary to perform feature extraction before model building. Researchers have found that, PLS (Partial Least Squares) [16, 17] is able to perfectly realize feature extraction from input to output. PLS is a standard multivariate regression method, which is to form components that capture most of the information in the explanatory variables that is useful for predicting dependent variables, while reducing the dimensionality of the regression problem by using fewer components than the number of explanatory variables. PLS technique is considered especially useful for constructing prediction equations when there are many explanatory variables, comparatively little sample data and the collinearity between independent variables. It also has strong anti-noise property and great generalization ability, it does not require obtaining the distribution model of the sample in advance, and it also has various characteristics such as a high predication precision, so it is also called the second-generation regression method. Inspired by the PLS and based on DV-Hop localization method, the paper makes use of PLS technique in multivariate regression to optimize DV-Hop algorithm, and proposes a PLS-based DV-Hop localization method (PLS-DVHop).

3 Brief Reviews of DV-Hop, PLS

Before the introduction of our algorithm, for completeness, we will briefly review DV-Hop and PLS in the next sub-sections.

3.1 DV-HOP

DV-Hop method does not require any hardware to measure ranges or angles to neighbours. It only relies on the connectivity of the underlying graph and it comprises three no overlapping stages:

1) First, each node estimates the least hop-counts to each beacon and maintains a table $[x_i, y_i, h_i]$ and exchanges updates only with its neighbours. Where $[x_i, y_i]^T$ denotes the physical location of beacon i, h_i is a counter to record the hop-counts to beacon. This phase is the classical Bellman-Ford distributed shortest path algorithm.

2) In the second stage, beacons cooperatively estimate the average distance of each hop in the network. Once a beacon j gets the hop count h_i to beacon i, it reports the value of h_i to beacon i. After collecting these values from all other beacons, beacon i (locating at $[x_i, y_i]^T$) calculates the average distance of each hop in the network, uses it as an adjusted value and broadcasts it to the network. The average distance of each hop can be expressed by the following equation:

$$HopSize_i = \frac{\sum_{i \neq j} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{\sum_{i \neq j} h_i}. \tag{1}$$

3) After receiving the correction, an arbitrary node may estimate distances to beacons. Suppose an unknown node receives the messages from three beacons, i.e. beacon i, j, and k. It uses the three distance estimates ($HopSize_i \times h_i$, $HopSize_j \times h_j$, and $HopSize_k \times h_k$) to determine its location by trilateration or maximum likelihood method.

3.2 PLS

Before regression, PLS makes use of covariance to guide feature extraction of input variable and output variable. In the process of extraction, information integration and screening technology is applied, so that PLS method overcomes correlation of input variable, eliminating the influence of co-linearity on regression. Moreover, in the process of regression, interpretation and prediction role of input on output is emphasized, which eliminates noise unfavourable to regression. As for this, PLS method leads to good robustness and prediction stability. PLS method always converts multivariate regression problem into several simple regression problems, so that it is also fit for small sample. Owing to such favourable natures, PLS is quite fit for WSN localization.

Linear PLS method comprehensively considers input variable **H** and output variable **D**, which solves component **t**, **u** (**t** is linear combination of variable **H**, and **u** is linear combination of variable **D**). The principle is shown in Figure 1:

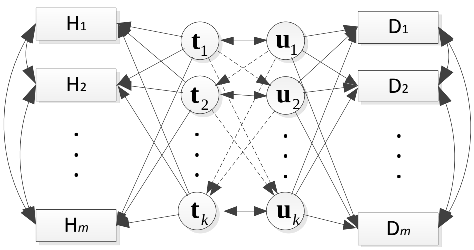


FIGURE 1 The schematic diagram of PLS

It may be seen from Figure 1 that, cross covariance between **H** and **D** is important information. Such cross covariance is hoped to be described through k. Thus, solution of PLS shall meet:

1) **t** and **u** shall try to carry variation information of their respective data sheet as much as possible.

2) The correlation between **t** and **u** may be maximized. PLS is described as solution of optimization problem:

$$\max \left\| \mathrm{cov}(\mathbf{t},\mathbf{u}) \right\|^2 = \max[\mathbf{Hw}, \mathbf{Dc}], \tag{2}$$

where, **w**, **c** is weight vector.

Basic steps of PLS algorithm is shown below:

Firstly, input and output variables are to be standardized, so as to eliminate influence on final calculation result caused by inconsistent dimension of input and output variable;

The first principle component $\mathbf{t}_1$ and $\mathbf{u}_1$ are separately extracted from input and output variable H, D. In accordance with the demand of regression, the below conditions shall be satisfied:

- $\mathbf{t}_1$ and $\mathbf{u}_1$, shall try to carry variation information of variable **H**, **D** as much as possible;
- Correlation between $\mathbf{t}_1$ and $\mathbf{u}_1$ shall be able to be maximized.

After extraction of the first component $\mathbf{t}_1$ and $\mathbf{u}_1$, regression of **H**, **D** on $\mathbf{t}_1$ shall be separately performed. If the regression equation has reached satisfactory precision, PLS method will be terminated. Or else, residual of **H** after being interpreted by $\mathbf{t}_1$, as well as residual of **D** after being interpreted by $\mathbf{u}_1$ will be utilized to perform the second round of component extraction. Repeat the process, until a satisfactory precision is obtained.

4 The establishment of PLS-DVHop localization model

The localization process of PLS-DVHop work in two phases: offline training phase and an online localization phase. More specifically, in the offline training phase, we take two steps for model building. In the first step, we collect hop-counts and Euclidean distances between beacons as the training set. In the second step, we make use of PLS technique to obtain the mapping model between hop-counts and Euclidean distances. In the online localization phase, the real-time hop-counts samples received from the beacons by the unknown node, and then the unknown node uses the mapping model obtained through the training to conduct location estimation.

Consider a WSN which is comprised of n sensor nodes $\{S_i\}_{i=1}^n$ deployed in a 2D geographic region. Without loss of generality, let the first m nodes be beacons whose locations are known, for all $i = 1,\ldots,m$, where $m << n$. For every pair of sensors S_i and S_j, h_{ij} denotes shortest hop-count and d_{ij} denotes Euclidean distances that sensor S_i receives from sensor S_j. After running for a period of time, we can obtain two matrices, *i.e.*, the shortest hop-counts matrix $\mathbf{H}=[\mathbf{h}_1,\ldots,\mathbf{h}_m]$ and the Euclidean distances matrix $\mathbf{D}=[\mathbf{d}_1,\ldots,\mathbf{d}_m]$, where $\mathbf{h}_i=[h_{i1},\ldots,h_{im}]^T$, $\mathbf{d}_i=[d_{i1},\ldots,d_{im}]^T$.

Considering the relationship Euclidean distances and hop-counts, and according to the multiple regression theory. We can obtain an equation, which can be expressed as:

$$\mathbf{D} = \mathbf{H}\boldsymbol{\eta} + \boldsymbol{\varepsilon}, \tag{3}$$

where, $\boldsymbol{\eta} = (\eta_1, \eta_2, \cdots, \eta_m)^T$ is the regression coefficient vector, $\boldsymbol{\varepsilon}$ is the errors vector.

In order to minimize the error, as well as for the convenience of computation, we often use quadratic sum of error as the judgment standard. In order to figure out the optimal relation between the hop-counts and Euclidean distances, we are to figure out the partial derivative of the quadratic sum of error, and assuming that it is 0, hereby:

$$\mathbf{H}^T \mathbf{H}\hat{\boldsymbol{\eta}} = \mathbf{H}^T \mathbf{D}. \tag{4}$$

It may be seen from Equation (2) that, there may be as well multiple correlations between variables in **H**, or the number of samples in **H** may be smaller than the number of variables. If so, forced calculation of Equation (2) may leads to invalid result. In addition, the precision of estimation value $\hat{\boldsymbol{\eta}}$ is not only related with input variable, but also related with output variable **D**. Input and target co-determines the prediction direction of $\hat{\boldsymbol{\eta}}$.

Algorithm1: PLS-DVHop Localization Algorithm

Input $\mathbf{H} = [\mathbf{h}_1, \mathbf{h}_2, \cdots, \mathbf{h}_m]$: hop-counts matrix of beacons; $\mathbf{D} = [\mathbf{d}_1, \mathbf{d}_2, \cdots, \mathbf{d}_m]$: Euclidean distances matrix of beacons; k : the number of principal element; $\{\mathbf{c}_i = (x_i, y_i)\}_{i=1}^m$: the location of beacons

output $\{\hat{\mathbf{c}}_i = (x_i, y_i)\}_{i=m+1}^n$: estimated location of the non-beacons

1 Centring matrix **H** and matrix **D**

2 *for* $j = 1, \cdots, k$

$\mathbf{u}_j$ = first column of $\mathbf{H}_j^T \mathbf{D}$

$\mathbf{u}_j = \mathbf{u}_j / \|\mathbf{u}_j\|$

repeat

$\mathbf{u}_j = \mathbf{H}_j^T \mathbf{D}\mathbf{D}^T \mathbf{H}_j \mathbf{u}_j$

$\mathbf{u}_j = \mathbf{u}_j / \|\mathbf{u}_j\|$

until convergence

$$\mathbf{w}_j = \frac{\mathbf{H}_j^T \mathbf{H}_j \mathbf{u}_j}{\mathbf{u}_j^T \mathbf{H}_j^T \mathbf{H}_j \mathbf{u}_j}$$

$$\mathbf{c}_j = \frac{\mathbf{D}_j^T \mathbf{H}_j \mathbf{u}_j}{\mathbf{u}_j^T \mathbf{H}_j^T \mathbf{H}_j \mathbf{u}_j}$$

$\hat{\mathbf{D}} = \hat{\mathbf{D}} + \mathbf{H}_j \mathbf{u}_j \mathbf{c}_j^T$

$\mathbf{H}_{j+1} = \mathbf{H}_j (\mathbf{I} - \mathbf{u}_j \mathbf{w}_j^T)$

end

$\hat{\boldsymbol{\eta}} = \mathbf{U}(\mathbf{W}^T \mathbf{U})^{-1} \mathbf{C}^T$

3 Putting the obtained estimation term $\hat{\boldsymbol{\eta}}$ into the original equation to figure out the prediction model; putting the hop-counts from unknown nodes to known nodes into the equation to further figure out corresponding estimation distance. At the moment, integrating coordinates and estimation distance of known nodes, least squares may be used to estimate unknown nodes, so as to obtain the estimation coordinates.

PLS is a multivariate data analysis method integrates multivariate regression, canonical correlation analysis and principle component analysis altogether. It makes use of covariance of input and output to guide feature selection, which perfect fits for modelling and prediction of real situation. Being applied in DV-Hop localization method, PLS is fit for different localization situation, and is able to obtain high localization accuracy. At the moment, hop-count and Euclidean distances modelling process based on PLS may be concluded as Algorithm 1.

5 Performance evaluations

One of the important features of range-free localization method is that, it is quite fit for large-scale deployment. This requires thousands of sensor nodes, while in labs; it is difficult to realize such large-scale real network. As for this, in researches on large-scale range-free node localization algorithm, software simulation is often applied to estimate the advantages and disadvantages of localization algorithm.

In this section, the performance of PLS-DVHop algorithm is to be analysed and assessed via simulation experiment. Matlab2013b software is employed to analyse and compare methods proposed in this paper. In the experiment, all nodes are evenly distributed in two-dimensional space. In order to reduce the one-sidedness of single experiment, each deployment goes through 50 simulations while nodes in each experiment are randomly re-distributed in the experiment area. Mean value of 50 RMS (Root Mean Squares) [18] is taken as the assessment basis.

In order to assess the performance of methods proposed in this paper, nodes are assumed to be randomly or regularly deployed in the monitoring area. In addition, in order to evaluate the adaptability of the proposed methods to network topology anisotropy, obstruction is added in the aforementioned two deployment strategies, i.e. assuming that there is a large obstruction in the deployment area, impeding the direct communication between nodes. Such area is of C-Shape. In allusion to different network topology structure, nodes are re-deployed in the same area for several times, assessing the average localization error. This experiment also compare our method with three previous methods:

1) The classic DV-Hop method proposed in [7];

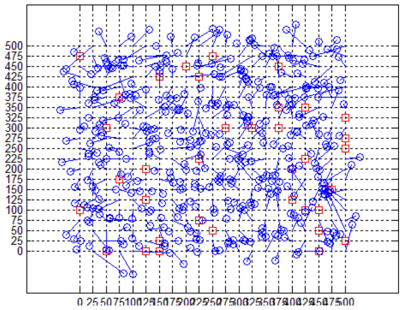
2) PDM proposed in [11];

3) LSVR proposed in [13] in two group experiments.

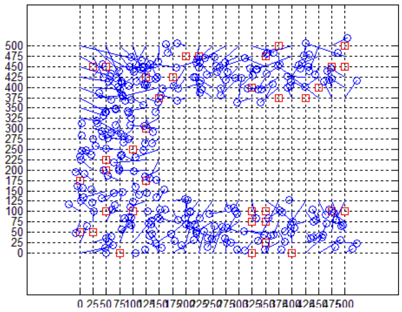
Furthermore, for fairness, in PDM localization, we denoted abandoning threshold in TSVD as 2, i.e. abandoning eigenvectors with eigenvalue less than or equal to 2. There is certain relationship between kernel parameter σ and the distance between training samples. In the experiment, we assume σ as 50 times of the average distance between sample nodes. Configuration of C and ε in SVR method uses for reference related reference [19], while C is also configured based on σ according to related reference [20]

5.1 REGULARLY DEPLOYED SENSORS

In this group of experiments, there are 441 and 315 nodes deployed in the area of square or C-Shape region. The number of beacons was gradually increased from 30 to 50, with a step size of 2.before analysing the performance of PLS-DVHop algorithm, let us first investigate the two final localization results (in figure the number of beacons is 36). In Figure 2, the circles denote the unknown node and the squares are the beacon node, the line connects the actual coordinate and estimated coordinate of unknown nodes, and the longer the line, the more the estimated value deviates from the actual location.



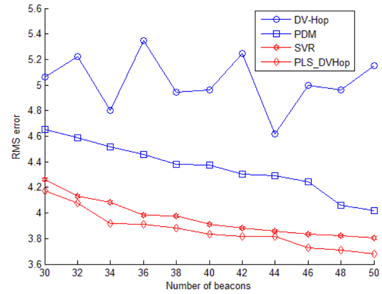
a) Square Regular Distribution



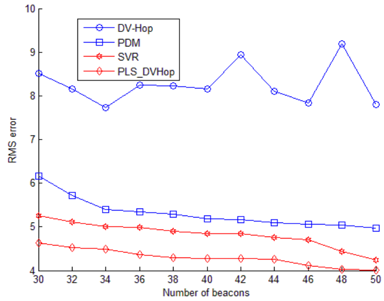
b) C-shaped Regular Distribution

FIGURE 2 Localization Results Under Regular Distribution

Figures 3a and 3b describes the influence of beacons quantity on localization accuracy in regular deployment network. Theoretically, more beacons in monitoring area leads to smaller localization error. According to the result shown in Figures 3a and 3b, RMS error of DV-Hop is the largest, and the curve fluctuates up and down. RMS error of the other three methods simply decreases with the number of beacons grows. PLS-DVHop algorithm proposed in this paper takes on highest localization accuracy. In addition, RMS error of PLS-DVHop and LSVR method are similar in the two deployment area. By contrast, the rest methods take on significant difference. This also shows that PLS-DVHop and LSVR methods have high environment adaptability, and are fit for anisotropic networks. As PLS-DVHop is multivariate regression method, in calculation process, it considers correlation between nodes. Thus, its localization accuracy is the highest. It may as well be seen from Figure 3 that, PLS-DVHop monotonically decreases with the number of beacon increases. Yet, such tendency is weak. This also indicates that, the number of beacons has quite slight influence on precision of the algorithm. PLS-DVHop method is also fit for environment with fewer beacons.



a) RMS error under Square Regular Distribution

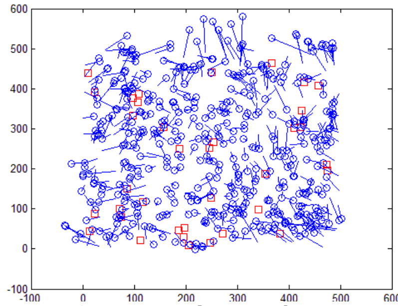


(b) RMS error under C-Shape Regular Distribution

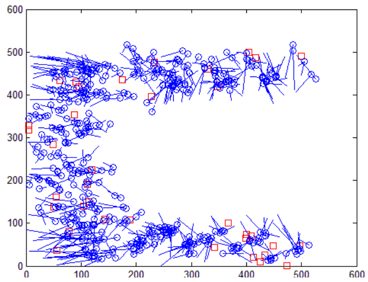
FIGURE 3 RMS error Under Regular Distribution

5.2 RANDOM DEPLOYED SENSORS

In this group of experiments, 500 nodes were randomly deployed in a 500×500 two-dimensional square area, and 30 to 50 nodes were chosen from the 500 as the beacon nodes. Like the regular deployment, in order to investigate the impact of non-line-of-sight on the localization algorithm, the experiment scenario with obstacle was added to the random deployment experiment. Similarly, the two final localization results were analysed first. As shown in Figure 4, in these two experiments, the number of beacon nodes is still 36.



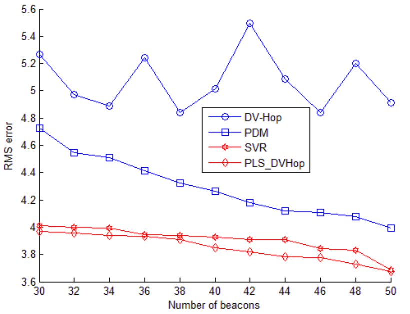
a) Square Random Distribution



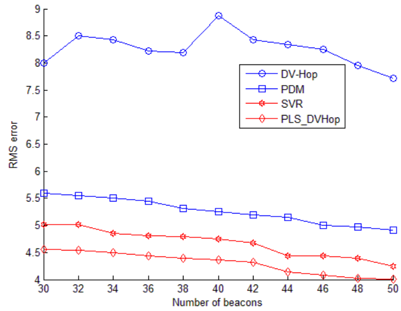
b) C-Shape Random Distribution

FIGURE 4 Localization Results Under Random Distribution

Figures 5a and 5b describes the relation between beacon quantity and RMS error in random deployment network. Similar to regular deployment, RMS error of DV-Hop is the highest, and the curve fluctuates up and down. Moreover, in C-shaped region, the localization error is larger than that in square region. This proves that, DV-Hop method is instable, and is sensitive to anisotropy of network topology. PDM method eliminates some data of small eigenvalue. As the elimination is set manually, disregarding factors of hop count and real distance dimension, its localization accuracy is only slightly improved than DV-Hop method. The localization accuracy of LSVR method is quite close to the method proposed in this paper. Yet, LSVR is a multi-input and single-output method, and is powerless when establishing inter-matrix relation like hop-counts and real distances. LSVR method has to perform frequent modelling. Although being optimized, it still does not considered correlation between data. Thus, the localization accuracy of SVR-based method is lower than the method proposed in this paper.



a) RMS error under Square random Distribution



b) RMS error under C-Shape random Distribution

FIGURE 5 RMS error Under random Distribution

6 Conclusions

In this paper, a range-free localization method (PLS-DVHop) is proposed. The method establishes the relation between hop-counts and Euclidean distances, so as to build measurement distance (hop-counts) and Euclidean distance model, and to effectively solve complicated topological structure problem in WSN. Compared with other similar methods, PLS-DVHop method inherits the advantages of DV-Hop method. Shown by simulation test, under different deployment environment, PLS-DVHop algorithm is able to present high positioning accuracy, and is only slightly affected by the number of beacon.

Acknowledgements

The paper is sponsored by Provincial University Natural Science Research Foundation of Jiangsu Education Department (12KJD510006, 13KJD520004); Natural Science Foundation of Jiangsu(BK2012082); Doctoral Scientific Research Startup Foundation of Jinling Institute of Technology (JIT-B-201411); Educational Reform Foundation of Jinling Institute of Technology(2010JGXM-02-2).

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