ABSTRACT: Location methods based on learning theory perform well in wireless cellular networks. These methods may be further improved since range measurements among all nodes are not taken into consideration, while these range measurements in the WSN location system are generally available. In this paper, we propose an improved LS-SVM based location algorithm to solve mobile location problem in a NLOS environment. We extend LS-SVM method from wireless cellular networks to WSN location system. Compared with LS-SVM in wireless cellular networks only using the range measurements between anchor nodes and blind nodes, the proposed method can improve the positioning accuracy by using all the range measurements among the nodes. Moreover, steepest descent method is used in the proposed method to iterative search the optimal position estimation of blind nodes. The simulations results in different cases illustrate that the proposed algorithm outperforms the kernel method and LS-SVM method on location accuracy.

KEYWORDS: Mobile location; Wireless Sensor Networks (WSN); Least Squares Support Vector Machine (LS-SVM); Steepest Descent Method
from a different angle than the direct path between blind nodes and anchor nodes, and for ranging measurements (or equivalently, time of arrival), it will add a large positive error in addition to standard measurement error [9]-[10]. Although many location methods such as NLOS identification algorithm [11], inequality constraint [12] and scatter information [13] were addressed to suppress NLOS errors, their performance improvement is not significant since all of these methods don’t consider the prior information on sample points. Based on the prior information of sample points, several learning location methods have been proposed to estimate the position of blind nodes [14]-[16] and obtain the higher positioning accuracy. The method in [14] first generates a NLOS correction map based on Krigeing method, and then uses the correction map to rectify the distorted blind nodes location. The method presented in [15] introduces the use of nonparametric kernel-based estimators for location of the blind nodes using measurements of propagation delays. Furthermore, a LS-SVM based location method in [16] is proposed to learn the relationship between the TOA measurements and the blind nodes location. All of these methods mentioned in [14]-[16] perform well in wireless cellular networks. These methods may be further improved since range measurements among all nodes are not taken into consideration, while these range measurements in the WSN location system are generally available. Thus, in this paper, we propose an improved LS-SVM based location algorithm to solve mobile location problem in a NLOS environment. We extend LS-SVM method from wireless cellular networks to WSN location system. Compared with LS-SVM in wireless cellular networks only using the range measurements between anchor nodes and blind nodes. The proposed method can improve the positioning accuracy by using all the range measurements among the nodes.

In general, learning algorithms consist of two phases: training and positioning. During the training phase, parameters of learning algorithms are estimated using measurements of training points. During the positioning phase the measurement of blind nodes is performed, and then the position of blind nodes can be computed using the parameters estimated in the training phase.

For simplification, we consider a TOA based WSN location system. Assuming that devices \((x_i, y_i), i=1,\ldots,M\) is the position of the \(i\)th anchor node with the known coordinates and devices \(\langle \tilde{x}_j, \tilde{y}_j \rangle, j=1,\ldots,N\) is the position of the \(j\)th training point and \(r_{ij}\) is the corresponding range measurement to the \(i\)th anchor node. Given a training data set of \(N\) points:

\[
D = \{(R_j, v_j) \mid j = 1, \ldots, N \}
\]

With input data \(R_j = [r_{j1} \cdots r_{jM}] \in \mathbb{R}^N\) and output data \(v_j \in \mathbb{R}\). In LS-SVM method, optimal problems can be described as [16]-[17]:

\[
\min J(w, e) = \frac{1}{2} w^T w + \frac{1}{2} \gamma \sum_{j=1}^{N} e_j^2
\]  

Subject to:

\[
v_j = w^T \phi(R_j) + b + e_j
\]

Where \(\phi() : \mathbb{R}^N \rightarrow \mathbb{R}^N\) is a nonlinear mapping in kernel space, weight vector \(w \in \mathbb{R}^N\), error variable \(e = [e_1 \cdots e_N]\), and \(b\) is a bias. \(J\) is a loss function and \(\gamma\) is an adjustable constant.

According to optimal function (2) and (3), we define the Lagrange function as:

\[
L(w, b, e, a) = \frac{1}{2} w^T w + \frac{1}{2} \gamma \sum_{j=1}^{N} e_j^2 - \sum_{j=1}^{N} a_j \{ w^T \phi(R_j) + b + e_j - v_j \}
\]

Where \(a_j\) are Lagrange multipliers, as support vectors \((a_j \in \mathbb{R})\). The conditions for optimality are given by:

\[
\begin{align*}
\frac{\partial L}{\partial w} = 0 & \rightarrow w = \sum_{j=1}^{N} a_j \phi(R_j) \\
\frac{\partial L}{\partial b} = 0 & \rightarrow \sum_{j=1}^{N} a_j = 0 \\
\frac{\partial L}{\partial e_j} = 0 & \rightarrow a_j = \gamma e_j \\
\frac{\partial L}{\partial a_j} = 0 & \rightarrow w^T \phi(R_j) + b + e_j - v_j = 0
\end{align*}
\]

From (5), and elimination of \(w\) and \(e\), we get the following matrix equations:

2 PROPOSED METHOD

In this section, we extend LS-SVM method from wireless cellular networks to WSN location system. Compared with LS-SVM in wireless cellular networks only using the range measurements between anchor nodes and blind nodes, the proposed method can improve the positioning accuracy by using all the range measurements among the nodes.

The rest of this letter is organized as follows. Section 2 presents the proposed algorithm, and Section 3 presents the simulation results. Finally, conclusion is given in section 4.
\[
\begin{bmatrix}
0 \\
1_N^T \\
1_M^T
\end{bmatrix}
\Omega + \frac{1}{\gamma} I
\begin{bmatrix}
a \\
b
\end{bmatrix} =
\begin{bmatrix}
0 \\
v
\end{bmatrix}
\tag{6}
\]

Where \(1_N = [1 \ldots 1]^T\), \(\Omega_{M} = \varphi(R_k)^T \varphi(R_l)\), \(k,l = 1, \ldots, N\), \(a = [a_1 \ldots a_N]^T\), \(v = [v_1 \ldots v_N]^T\).

According to Mercer’s condition, there is mapping \(\varphi(\bullet)\) and kernel function:

\[
K(R_k, R_l) = \varphi(R_k)^T \varphi(R_l)
\tag{7}
\]

Assuming that \((\hat{x}_j, \hat{y}_j)\) is the position estimation of the \(j\)th blind node, \((x_j, y_j)\) is the true position of the \(j\)th blind node, \(r_{ji}\) is the range measurement to the \(i\)th anchor node. \(R_j = [r_{j1} \ldots r_{jm}]\) is the corresponding vector of range measurements. During the position phase, the location of blind nodes can be obtained:

\[
v(R_j) = \sum_{i=1}^{N} a_j K(R_j, R_i) + b
\tag{8}
\]

Where the parameters \(a_j\) and \(b\) can be obtained by solving (6). Kernel function has different types, such as poly-nominal, MLP, splines, RBF and so on. We will focus on RBF kernel which corresponds to [5][16]:

\[
K(R_k, R_l) = \exp(-\frac{||R_k - R_l||^2}{2\sigma^2})
\tag{9}
\]

The position estimation of blind nodes by (8) may be further improved since range measurements among all nodes are not taken into consideration, while these range measurements in the WSN location system are generally available. Thus, in order to improve the localization accuracy of blind nodes in the WSN location system, we can use the range measurements between anchor nodes and blind nodes and steepest descent method to iterative search the optimal position estimation of blind nodes.

Calculate the distance among the position estimation of blind nodes.

\[
\hat{r}_j = \sqrt{(\hat{x}_j - \bar{x}_j)^2 + (\hat{y}_j - \bar{y}_j)^2}
\tag{10}
\]

Where \((\hat{x}_j, \hat{y}_j)\) is the position estimation of the \(j\)th blind node.

The following criterion is used to determine the line-of-sight (LOS) path:

\[
\hat{r}_j - r_j \leq \xi \sigma_{nj}
\tag{11}
\]

Where \(\hat{r}_j = \sqrt{(x_j - x_{\hat{j}})^2 + (y_j - y_{\hat{j}})^2}\) is the corresponding range measurement between the \(i\)th anchor node and the \(j\)th blind node, \(n_{ij}\) is the standard range measurement noise and is subject to Gaussian distribution with zero-mean and variance \(\sigma_{nj}^2\), \(\xi\) is the discriminant coefficient. When (11) holds, the \(\hat{r}_j\) will be added to LOS range measurement set \(L\).

The size of LOS range measurement set \(L\) is affected by \(\xi\), because the value of \(\xi\) determine \(\hat{r}_j\) whether or not add to LOS range measurement set \(L\). Normally distributed data assumes that about 99% of the values in the sample are within 2.58 standard deviation of the mean. We assume that the more blind nodes in the LOS path, so in our simulation, we choose:

\[
\xi = 2.58
\tag{12}
\]

According to formula (10) and (11), we can define the cost function of distance vector:

\[
J = \sum_{i=1}^{K} \sum_{j=1}^{K} (\hat{r}_j - r_j)^2
\tag{13}
\]

Where \(\hat{r}_j \in L\), and \(K\) is the number of elements for LOS range measurement set \(L\).

Substituting (13) into \(\frac{\partial J}{\partial \hat{x}_i}\) and \(\frac{\partial J}{\partial \hat{y}_i}\), gives:

\[
\frac{\partial J}{\partial \hat{x}_i} = \sum_{j=1}^{K} (\hat{r}_j - r_j) \frac{\hat{x}_j - \bar{x}_j}{\hat{r}_j} \frac{\partial \hat{x}_j}{\partial \hat{x}_i}
\]

\[
\frac{\partial J}{\partial \hat{y}_i} = \sum_{j=1}^{K} (\hat{r}_j - r_j) \frac{\hat{y}_j - \bar{y}_j}{\hat{r}_j} \frac{\partial \hat{y}_j}{\partial \hat{x}_i}
\tag{14}
\]

From (14), the steepest descent method is used to iteratively search the optimal position estimation of the \(i\)th blind node:

\[
[\hat{x}_{i-1} \hat{y}_{i-1}] = [\hat{x}_{i-1} \hat{y}_{i-1}] - u \begin{bmatrix}
\frac{\partial J}{\partial \hat{x}_{i-1}} \\
\frac{\partial J}{\partial \hat{y}_{i-1}}
\end{bmatrix}
\tag{15}
\]

Where \(u\) is the step size, \(m\) is the number of iterations.

To sum up, here are the steps:

1. Given training data
   \[D = \{(R_j, v_j)\}_{j=1}^{N}\]
   calculate \(a = [a_1 \ldots a_N]^T\) and \(b\) from (6).
2. Calculate the position estimation of blind nodes from (8).
3. From (10), calculate the distance among the position estimation of blind nodes.
3 SIMULATION RESULTS

Assuming in a Manhattan-like urban environment, the geometry of anchor nodes with the known coordinates configuration is shown in Fig. 1. The square regions of dimensions represent buildings, and the other regions represent streets. This configuration is used since similar configurations have been used to evaluate other blind nodes location schemes [10] [14]-[15]. The coordinates of Anchor nodes are \( m \), \( m \), \( m \). The training points are uniformly distributed in the street, and the positions of ten blind nodes are randomly deployed. The standard range measurement error of TOA, brought by the measurement equipment, could be modeled as a Gaussian random variable with zero-mean.

In this section simulation, to compare with the proposed methods, kernel method [15] and LS-SVM method [16] are selected here due to them wide application in the WSN location system.

The position error of blind nodes is obtained from the average of 500 independent runs, and shown as:

\[
MLE = E[\sqrt{(\bar{x}_i - x_i)^2 + (\bar{y}_i - y_i)^2}]
\]  

(16)

3.1 Performance comparison with different number of training points

In this simulation, Fig. 2 is performed to study the effects of the number of training points on the WSN location system. The number of training points is varied from 10 to 80, and the standard range measurement error is 30m. It can be seen from figure that the mean location error decreases with the number of training points and the proposed method provides much better performance than the kernel method and LS-SVM method.

3.2 Performance comparison with different standard range measurement error

In this simulation, for a practical system it is interesting to study the impacts of the standard deviations of range measurements. Fig 3, shows the MLE versus standard deviations of range measurements when the number of training points is 50. The standard deviations of range measurements are varied from 10m to 30m. It can be observed from figure that the mean location error increases with the standard deviations of range measurements and the proposed method outperforms the kernel method and LS-SVM method. As the range noise becomes small, the positioning accuracy of the proposed method increases.

4 CONCLUSIONS

Although location methods based on learning theory perform well in NLOS environments wireless cellular networks, these methods may be further improved since range measurements among all nodes are not taken into consideration, while these range measurements in the WSN location system are generally available. In order to overcome this shortcoming, we propose an improved LS-SVM
based location algorithm in this paper to solve mobile location problem in a NLOS environment. A comparison is performed between the proposed method and two other learning methods (kernel method and LS-SVM method). The simulations results in different cases illustrate that the proposed algorithm outperforms the kernel method and LS-SVM method. As a result, the proposed algorithm can enhance the positioning accuracy and obtain reliable positioning information.

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