A NOVEL INDOOR GEO-LOCATION METHOD USING MIMO ARRAY

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Abstract In a Multiple-Input Multiple-Output (MIMO) Orthogonal Frequency Division Multiplexing (OFDM) based Wireless Local Area Network (WLAN) system, both Access Points (APs) and Mobile Terminals (MTs) are configured with multiple antennas, to make novel indoor geo-location method possible. In this paper, we presented a novel Least Square Support Vector Machine (LS-SVM) based data fusion algorithm to fuse signal strength measurements for indoor geo-location using only a single AP with MIMO arrays. We evaluate our proposed algorithms under indoor environments by MATLAB simulations. Simulation results show that our MIMO-based algorithm is superior to conventional least square algorithm.

Key words Indoor geo-location; Multiple-Input Multiple-Output (MIMO); Least Square Support Vector Machine (LS-SVM); Wireless Local Area Network (WLAN)

I. Introduction

Accurate indoor geo-location is an important component of ubiquitous computing for commercial, public safety and military applications[1]. However, it is a challenging job for designers due to the complexity of indoor radio propagation and the ad hoc nature of the deployed infrastructure in these areas. All of current indoor geo-location methods rely on more than three Access Points (APs). They could detect signal measurements from an unknown mobile terminal simultaneously[1]. However, due to the complexity of indoor radio propagation, it is often expensive and also difficult to be satisfied. As a result, we proposed a data fusion based indoor geo-location method using only a single AP with Multiple-Input Multiple-Output (MIMO) antennas array, although more access points could achieve higher accuracy. In this paper, we attempted to propose a novel indoor geo-location method for such system using a data fusion model based on Bayesian inferring and Least Square Support Vector Machine (LS-SVM) algorithm[2]. The method presented here is based on signal strength measurements because of its ubiquitous availability in practical available receivers in the market, and it can also be extended to other measurements including Time-Difference-Of-Arrival (TDOA), Time-Of-Arrival (TOA), Angle-Of-Arrival (AOA). The application of MIMO antenna arrays to the WLAN system provides the potentials for novel location techniques based on data fusion.

II. Data Fusion Model for Positioning

Our data fusion model with MIMO arrays for indoor geo-location is illustrated in Fig.1.

In this model, we first fuse several Received Signal Strength Indicator (RSSI) measurements from \(M\) emitter antennas through linear Bayesian inferring, and the first fusion results can be represented as:

\[
X_{oj} = \hat{o}_{opt} X_{ji}, \quad \hat{o}_{opt} = \left( \begin{array}{c} \frac{1}{\delta_1^2} \\frac{1}{\delta_2^2} \cdots \frac{1}{\delta_M^2} \end{array} \right)^T
\]

where, \(X_{ji}\) is the measurement value on receiver antenna \(j\) from emitter antenna \(i\), and \(\delta_i\) is responding variance of \(X_{ji}\), which could be derived through channel estimation. We simplify it as:

\[
\delta_i = X_i - \text{median}(X_1, \cdots, X_M)
\]

Then the output measurements are sent to the second fusion center, employing an LS-SVM algorithm to fuse them through learning and testing[2]. In the end, we could derive unknown position of the Mobile Terminal (MT) based on only a single AP with MIMO array.
III. LS-SVM Algorithms

Originally, SVM has been introduced within the context of statistical learning theory and structural risk minimization, employed to solve convex optimization problems, typically quadratic programs\[^{[3]}\]. LS-SVMs are reformulations to the standard SVMs, which lead to solving linear KKT systems\[^{[2]}\]. Here, we simply introduce the function estimation algorithm LS-SVMs:

Given a training data set of \( N \) points \( D = \{(x_i, y_i) | k = 1, 2, \ldots, N\} \) with input data \( x_i \in \mathbb{R}^n \) and output data \( y_i \in \mathbb{R} \), the following optimization problem is considered in primal weight space. In the algorithm LS-SVM:

\[
\text{minimize } J(w, e) = \frac{1}{2} w^T w + \frac{1}{2} \gamma \sum_{k=1}^{N} e_k^2
\]

Subject to

\[
y_k = w^T \varphi(x_k) + b + e_k, \quad k = 1, \ldots, N
\]

where \( \varphi() : \mathbb{R}^n \rightarrow \mathbb{R}^m \) is a nonlinear mapping in kernel space, \( w \in \mathbb{R}^m \), error variable \( e_k \in \mathbb{R} \) and \( b \) is bias. \( J \) is loss function, and \( \gamma \) is an adjustable constant. The aim of the mapping function in kernel space is picking out features from primal space and mapping training data into a vector of a high dimensional feature space, in order to solve the problem of nonlinear regression.

According to optimal function Eq.(2), we define the Lagrangian function

\[
L(w, b, e, \alpha) = J(w, e) - \sum_{k=1}^{N} \alpha_k \{ w^T \varphi(x_k) + b + e_k - y_k \}
\]

where \( \alpha_k \) are Lagrange multipliers, which are also support vector \((\alpha_k \in \mathbb{R})\). The optimality of upper function is as the following sets of linear equations instead of quadratic program in traditional SVMs.

\[
\begin{align*}
\frac{\partial L}{\partial w} &= 0 \rightarrow w = \sum_{k=1}^{N} \alpha_k \varphi(x_k) \\
\frac{\partial L}{\partial b} &= 0 \rightarrow \sum_{k=1}^{N} \alpha_k = 0 \\
\frac{\partial L}{\partial e_k} &= 0 \rightarrow \alpha_k = \gamma e_k \\
\frac{\partial L}{\partial \alpha_k} &= 0 \rightarrow w^T \varphi(x_k) + b + e_k - y_k = 0 \\
&\quad \text{for } k = 1, \ldots, N
\end{align*}
\]

After eliminating variables \((w, e)\) we get matrix form as Eq.(5).

\[
\begin{bmatrix}
0 \\
1_v^T \\
1_v \\
\Omega + \frac{1}{\gamma}I
\end{bmatrix} [\alpha] = \begin{bmatrix}
0 \\
b
\end{bmatrix}
\]

where \( y = [y_1 \cdots y_N] \), \( 1_v = [1 \cdots 1] \), \( \alpha = [\alpha_1 \cdots \alpha_N] \) and \( \Omega_{ij} = \varphi(x_i)^T \varphi(x_j), \quad k, l = 1, \ldots, N \). According to Mercer’s condition, there is mapping \( \varphi \) and kernel function

\[
K(x_i, x_k) = \varphi(x_i)^T \varphi(x_k)
\]

which cause such

\[
y(x) = \sum_{k=1}^{N} \alpha_k K(x, x_k) + b
\]

where \( \alpha, b \) are obtained by solving Eq.(5). Kernel function has different types, such as poly-nominal, MultiLayer Perceptron (MLP), Splines, Radius Margin Bounds (RMF) and so on. The precision and convergence of LS-SVMs are affected by \((\gamma, \sigma)\).

There are only two parameters to be tuned: the kernel setting and \( \gamma \). In our simulations, we choose \( \gamma = [1 \ 1.2], \sigma = [0.87 \ 0.85] \). Generally, a grid search using leave-10-out cross-validation is used for tuning these two parameters\[^{[4]}\].

Grid search algorithm is as following\[^{[4]}\]:

1. For each set of the parameters, leave-10-out cross-validation on the training set is performed to predict the prediction error.

2. Select the set of values of the parameters that produced the model that gave the smallest prediction error (optimal parameter settings).

3. Train the model with the optimal parameter settings with the whole training set and test it with a test set (test is not used for training).

IV. Simulations

Our simulation is practically based on an important indoor environment and MIMO channel model described in Ref.[5]. A log-normal shadowing channel model is given by

\[
p_j = p_0 - 10n \log \left( \frac{d_i}{d_0} \right) + X_j + \varepsilon_j + e_j
\]

where \( p_j \) is the received power at device \( i \) transmitted by device \( j \), \( p_0 \) is the received power at a reference distance \( d_0 \), \( n \) is the path loss exponent, \( d_j \) is the path length, and \( X_j \) is the fading error\[^{[5]}\]. Here, \( \varepsilon_j \) is a zero mean Gaussian random variable with variance \( \sigma^2 \) (\( \sigma \approx 4 \text{dB} \) for indoor environments), and \( e_j \) is a random variable representing the effect of Non-Line-Of Sight (NLOS) propagation, \( e_j \) has a value from 10 to 20dB\[^{[5]}\].