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Indoor localization via ℓ^1-graph regularized semi-supervised manifold learning

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Abstract

In this paper, a new ℓ^1-graph regularized semi-supervised manifold learning (LRSML) method is proposed for indoor localization. Due to noise corruption and non-linearity of received signal strength (RSS), traditional approaches always fail to deliver accurate positioning results. The ℓ^1-graph is constructed by sparse representation of each sample with respect to remaining samples. Noise factor is considered in the construction process of ℓ^1-graph, leading to more robustness compared to traditional *k*-nearest-neighbor graph (KNN-graph). The KNN-graph construction is supervised, while the ℓ^1-graph is assumed to be unsupervised without harnessing any data label information and uncovers the underlying sparse relationship of each data. Combining KNN-graph and ℓ^1-graph, both labeled and unlabeled information are utilized, so the LRSML method has the potential to convey more discriminative information compared to conventional methods. To overcome the non-linearity of RSS, kernel-based manifold learning method (K-LRSML) is employed through mapping the original signal data to a higher dimension Hilbert space. The efficiency and superiority of LRSML over current state of art methods are verified with extensive experiments on real data.

Keywords ℓ^1-graph, indoor positioning, semi-supervised, manifold learning, wireless local area network (WLAN)

1 Introduction

Recently, WLAN has gained significant interest on how to design accurate and low cost sensor localization system for many personal and commercial applications [1–2]. There are three major calculating metrics in WLAN: time of arrival, angle of arrival, and RSS. Among these algorithms, RSS-based methods have been extensively studied as an inexpensive solution for indoor positioning system [3–4]. Compared to other algorithms, RSS can be easily obtained by WLAN integrated mobile device without any additional hardware modification.

The RSS information can be utilized in two different ways for indoor localization applications [5]. One is the physical radio propagation model. Because of the complexity of the radio propagation in the indoor scenario [6], the model always can not be precisely described. The other is called as fingerprint method. A database of RSS signals with labeled location information is initially collected. This process is finished at the offline stage, and the database is treated as the training set for statistical learning models [6–7]. Then, at the online stage, the model constructed at the offline stage is used to estimate the location from a new given RSS signal. This technique, known as fingerprinting, generally overcomes several limitations of the above mentioned propagation-based approaches, especially in complex scenarios. The key technical challenge in fingerprint-based localization method is how to map the RSS signal received from access points (APs) to a spatial position in 2D Cartesian coordinates [8], which can be described as the mapping rule $\boldsymbol{H}(\cdot): \boldsymbol{R}^m \to \boldsymbol{R}^2$. In order to model this mapping, lots of pattern matching methods are proposed. One simple

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solution is the KNN method [9], which estimates the position by computing the k closest neighbors with k smallest Euclidean distances with respect to the offline collected RSS database. Statistical method is proposed to estimate the probability of RSS signal at each potential position, such as maximum likelihood (ML) algorithm [10]. Kernel method [11] is another solution which maps the original RSS vector into a kernel feature space for better estimation.

Except for the localization precision factor, computational complexity and the storage capacity are also need to be jointly considered. Researchers have studied lots of ways to reduce the computing cost. Such as spatial filtering [4] and offline clustering method [10–12]. However, there remains two challenging problems faced by complex indoor scenarios. One is the AP selection problem. Due to wide deployment of APs, the dimension of the RSS vector is generally much higher than the three dimensional spatial coordinates needed for positioning. The other problem is the inevitable data noise generated due to several kinds of reasons, such as severe multipath, shadowing conditions, non-line-of-sight (NLOS) propagation or the effect of user body shadow in real applications. All methods mentioned above focus on modeling a map using the original RSS data without considering data noise, so the model constructed using contaminated data directly is not accurate. In this paper, a ℓ^1-graph regularized semi-supervised manifold learning method is proposed to mapping the initial high dimensional data into a low dimensional space which uncovers the nature structure of RSS data. Meanwhile, by introducing ℓ^1-graph into our approach, the system is more robust to data noise.

Our work is inspired in part by the prowess of compressive sensing (CS) [13] and Kernel method [14]. The novelties and contributions of the proposed methods are:

1) ℓ^1-graph is used as an extra regularization term to the objective function to reduce the influence of data noise, the original KNN-graph is biased by ℓ^1-graph.

2) Both labeled and unlabeled information are utilized in the process of semi-supervised manifold learning, which has the potential to convey more discriminative information compared to traditional manifold learning methods.

3) Kernel trick is used by mapping the signal space $\boldsymbol{R}^m$ to a Hilbert space H through a nonlinear mapping function $\Phi : \boldsymbol{R}^m \rightarrow \boldsymbol{H}$. The performance and generalization capability of the indoor positioning system are greatly improved.

The rest of this paper is organized as follows. Sect. 2 proposes the overall positioning system, and describes the interactions between the location server and the mobile device. Sect. 3 details our semi-supervised manifold learning process. The regularized ℓ^1-graph makes the system more robust to data noise. Kernel trick is used to overcome the non-linearity of RSS data. Extensive experiments are presented to show the robustness and superiority of our approach over other state-of-the-art methods in Sect. 4. Finally, Sect. 5 gives a conclusion.

2 System overview

The proposed system consists of mobile users and the location server. Fig. 1 illustrates the overall structure of the proposed system.

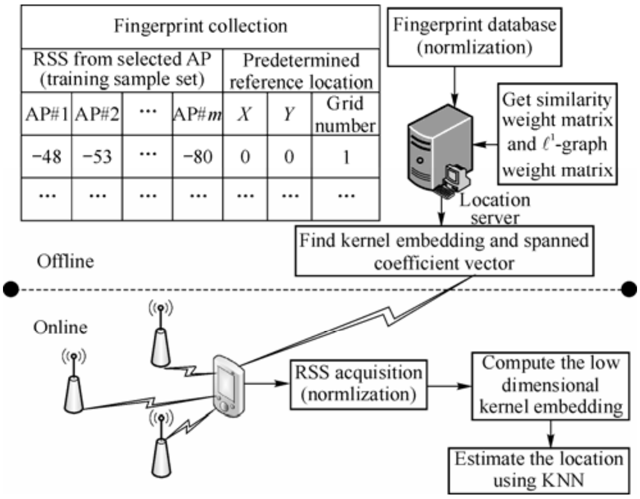

Fig. 1 System overview

At the offline stage, the mobile users collect the RSS fingerprints from APs. The location server constructs a fingerprint database (radio-map) including RSS signals at predetermined reference locations from all selected APs in the vicinity. The location server use the LRSML algorithm described in Sect. 3 to get the kernel embedding of every training sample and the spanned coefficient vector over these training samples. At the online stage, the localization of the mobile user is achieved in three steps: local collection of the RSS fingerprints, computing the low dimensional kernel embedding and estimating the position by k-nearest neighbor (KNN) method with respect to the kernel embeddings of the training data. The detail could be found in Sect. 3. The mobile users can locate themselves