

# Axial-Decoupled Indoor Positioning Based on Location Fingerprints

Wei Yanhua<sup>(✉)</sup>, Zhou Yan, Wang Dongli, and Wang Xianbing

Institute of Control Engineering, Xiangtan University, Xiangtan 411105, China  
358494653@qq.com

**Abstract.** Indoor positioning using location fingerprints, which are received signal strength (RSS) from wireless access points (APs), has become a hot research topic during the last a few years. Traditional pattern classification based fingerprinting localization methods suffer high computational burden and require a large number of classifiers to determine the object location. To handle this problem, axial-decoupled indoor positioning based on location-fingerprints is proposed in this paper. The purpose is to reduce the decision complexity while keeping localization accuracy through computing the position on X- and Y-axis independently. First, the framework of axial-decoupled indoor positioning using location fingerprints is given. Then, the training and decision process of the proposed axial-decoupled indoor positioning is described in detail. Finally, pattern classifiers including the least squares support vector machine (LS-SVM), support vector machine (SVM) and traditional k-nearest neighbors (K-NN) are adopted and embedded in the proposed framework. Experimental results illustrate the effectiveness of the proposed axial-decoupled positioning method.

**Keywords:** Location fingerprint · Axial-decoupled · Indoor positioning · Pattern classification

## 1 Introduction

With the popularity of wireless networks, the rapid growth of intelligent mobile phones and increasing maturity of pervasive computing technology, location based services (LBS) have attracted more and more attention and shown great popularity in many applications, such as indoor positioning, tracking, navigation, and location-based security [1–3]. The common positioning system such as the Global Positioning System (GPS) doesn't perform very well in urban settings especially inside buildings with a limited line-of-sight (LOS) from satellites. Because of the complexity of the indoor environment, it is usually difficult to provide a satisfactory level of accuracy in most applications. Therefore, one of the major challenges is to design real-time and accurate indoor positioning systems that can be easily deployed on commercially available

---

This work was supported by the National Science Foundation (NNSF) of China (under Grant 61100140 and 61104210) and the Construct Program of the Key Discipline in Hunan Province.

© Springer Nature Singapore Pte Ltd. 2016

T. Tan et al. (Eds.): CCPR 2016, Part I, CCIS 662, pp. 13–26, 2016.

DOI: 10.1007/978-981-10-3002-4\_2

mobile devices without any hardware installation or modification. Indoor positioning systems could be used to give access to an interactive map of a building. For instance, they could locate a person through an airport to the boarding gate, help a person find her room or facilitate the way of finding items of a shopping list in a supermarket.

There have been a variety of studies on indoor localization. As far as the indoor localization method is concerned, it can be categorized by the measurable quantities obtained from the transmitted signals. Received signal strength (RSS)-based localization methods have been extensively studied as an inexpensive solution for indoor positioning in recent years [4–6]. Compared with other methods based on algorithms (e.g., time-of-arrival (TOA) or angle-of-arrival (AOA) methods of UWB signals), RSS can be easily obtained by a Wi-Fi integrated mobile device, without any hardware installation or modification [7]. Various RSS-based indoor positioning and tracking algorithms have been proposed using the location information of access points (APs), which may not be available or hard to obtain in practice [8]. The major challenge for accurate RSS-based location comes from the variations of RSS due to the dynamic and unpredictable nature of radio channel by the structures within the building, such as shadowing, multipath, the orientation of wireless device, etc. [9]. Then, another approach is to pre-built radio map, termed as fingerprinting, to localize a mobile device [10], instead of using a propagation model to describe the relationship between RSS and position [11, 12]. Therefore, an implementation of an indoor positioning system based on fingerprinting signals of wireless local area networks (WLANs) has been proposed to estimate a location for indoor areas.

The location fingerprinting technique connects location-dependent characteristics (e.g. RSS) with grids in the region of interest (ROI) through measuring signals from available APs without knowing their location in advance, and uses these characteristics to infer the location [13–15]. At present, the location fingerprint positioning has attracted great attention of many researchers. The localization problem under this framework can be modeled as a pattern classification problem since at each time instant the user is located at a specific point in space [16, 17]. Commonly, the service area is pre-partitioned into a set of regions (e.g., a grid of cells); each serves as a class and a multi-class classification tool is used to assign a given fingerprint into one of these classes. A class of popular localization algorithms is based on pattern classification techniques including k-nearest neighbors (K-NNs), neural networks (NNs) and support vector machines (SVMs) etc. To name a few, Zhu et al. [18] introduce grid concept, changed position matching into multi-class classification problem and obtain the object location by SVM. Feng et al. [5] propose an accurate RSS-based indoor positioning system using the theory of compressive sensing, which is a method to recover sparse signals from a small number of noisy measurements by solving an  $l_1$ -minimization problem. In [19], Shin et al. propose a fingerprint positioning multi-classifier model on WLAN, making use of many results based on Bayesian combination rule [20] and majority vote [21] to obtain the fingerprint position. In [22], Xiang et al. propose a scalable semi-supervised learning (3SL) technique for building accurate fingerprinting from a small portion of labeled samples. Dortz et al. [23] propose a new method that compares online and offline signal strength probability distributions in order to find the nearest offline locations.

Traditional pattern classification based fingerprinting localization methods suffer high computational burden and require a large number of classifiers to determine the object location [24–26]. To handle this problem, axial-decoupled classification model is proposed in this paper for indoor positioning using RSS fingerprinting. The purpose is to reduce the decision complexity while keeping localization accuracy through computing the position on X- and Y axis independently, which can reduce the number of classifiers. Experimental results illustrate the effectiveness of the proposed axial-decoupled positioning method.

The rest of the paper is organized as follows. In Sect. 2, the problem of fingerprint based indoor localization framework is formulated. In Sect. 3, the proposed axial-decoupled method for localization is given, which followed by experimental results on both small-size and large-size dataset are included in Sect. 4. Section 5 concludes the paper with future researching directions given.

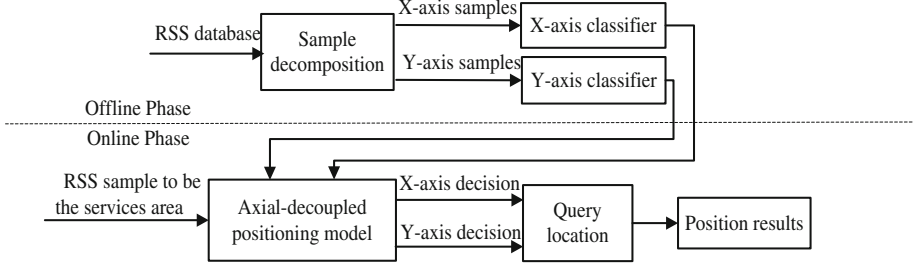
## 2 Problem Formulation

Considering a typical indoor positioning scenario, where a user carries a mobile device equipped with a WLAN adapter, using only RSS measurements from available APs. The location of these APs is unknown. The main task of the positioning system is to estimate the user's current location and illustrate it on a map (floor plan) on the device.

The location of the mobile is estimated by comparing the current RSS reading with a restored database called fingerprints, which is a table of measured RSS from a similar device over a grid of points. Several methods can be adopted to compare the RSS reading with the fingerprints. In this paper, axial-decoupled indoor positioning based on location-fingerprints is proposed. As depicted in Fig. 1, the proposed positioning system of axial-decoupled consists of two stages: offline phase (also known as training phase) and online phase (also known as positioning phase). In the offline phase, according to the site-surveying, the RSS from multiple APs at different grid points are collected and stored in a fingerprint database. The vector of mean RSS values at point on the grid is called the location fingerprint of that point. The fingerprint sample is then compared with fingerprints stored in the radio map for determining the location of the mobile devices on the grid.

Offline phase includes the following steps:

- I. Partition the ROI into a grid of cells, each cell receives RSS samples from wireless APs in order to build RSS feature vectors, and the sample is divided into X- and Y-axis training samples;
  - II. Using a normalized X- and Y-axis training sample to train classifier independently and obtained X-axis and Y-axis classifier.
- Online phase includes the following steps:
- III. A user carries a mobile device equipped with a WLAN adapter and enters the ROI, collecting RSS sample from wireless APs at the current position. Then, using the collected RSS sample as offline trained X- and Y-axis classifier input. Therefore, the X- and Y-axis decision results are obtained independently;
  - IV. Combining the X- and Y-axis decision results to locate mobile device.



**Fig. 1.** Axial-decoupled for indoor positioning classification model based on location fingerprints

### 3 Axial-Decoupled Positioning

#### 3.1 Offline Phase

During the offline phase, the samples of RSS readings are collected from known locations, referring to the reference points (RPs), by pointing the mobile device to different orientations. When considering an indoor positioning system covered with a WLAN in a single floor inside a building, we assume that there are  $N$  APs in the area and they are all visible throughout the area under consideration. A ROI is defined over the two dimensional floor plan. Assuming the ROI is partitioned as a  $l_x \times l_y$  grid according to the X- and Y-axis, we have  $l = l_x \cdot l_y$  grids in the area.

In each grid, the mobile users collect the RSS fingerprints from different APs and represented as a vector  $\{\bar{f}_i = (rss_1^i, rss_2^i, \dots, rss_n^i, \dots, rss_N^i)\}_{i=1}^w$ , consisting of  $w$  fingerprints sample at location with known coordinates, where  $rss_n^i$  is a RSS value corresponding to the  $i$ -th sample of the  $n$ -th AP's RSS value and  $N$  is the total number of available wireless APs. The sample of RSS feature vectors is denoted as  $f_{(m_i, n_i)} = (\bar{f}_i, m_i, n_i)$ , where  $m_i$  and  $n_i$  are respectively corresponded to the  $i$ -th sample of the grid in the X- and Y-axis of the class number, and  $m_i = 1, 2, \dots, l_x, n_i = 1, 2, \dots, l_y$ . The sample fingerprint collection of the X- and Y-axis, i.e.  $f_{x_i} = (\bar{f}_i, m_i)$ ,  $f_{y_i} = (\bar{f}_i, n_i)$ . Next, using the above two kinds of samples to train the multi-classifier respectively, and the axial-decoupled indoor positioning classification model is obtained. This lays a foundation for the online positioning phase.

#### 3.2 Online Phase

During the online phase, a user carries a mobile device equipped with a Wi-Fi adapter and enters the ROI, collecting RSS sample from wireless APs at the current position. The online RSS reading is compared with fingerprints stored in the database to determine the current localization by X- and Y-axis classifier independently. Following the positioning result of the X- and Y-axis is obtained jointly by the classifying decision.

For example, at the current position  $(x_k, y_k)$ , the collected RSS fingerprint is  $\bar{f}_k = (rss_1, rss_2, \dots, rss_n, \dots, rss_N)$ . The RSS fingerprints as the input of the trained offline on X- and Y-axis classifier, and to become the decision result on X- and Y-axis respectively. Next combine the results on both axes to locate the mobile device. The procedure steps are as follows:

- (i) The predicted class  $(m_x^k, n_y^k)$  of the test sample  $\bar{f}_k$  is obtained by X- and Y-axis classifiers, which are trained in the offline phase.
- (ii) The grid is determined by predicted class and the grid centroid is the predicted coordinate  $\hat{P}_k, \hat{P}_k = (\hat{x}_k, \hat{y}_k)$ .
- (iii) Adopting the 2-norm to calculate the deviation between prediction coordinate and the actual coordinate. The location accuracy  $A$  is denoted as:

$$A = \|\hat{P}_k - P_k\| \quad (1)$$

where  $P_k$  means the actual coordinates of the  $k$ -th test sample,  $P_k = (x_k, y_k)$ ;  $\|\cdot\|$  means a vector of 2-norm,  $\|\hat{P}_k - P_k\| = \sqrt{(\hat{x}_k - x_k)^2 + (\hat{y}_k - y_k)^2}$ .

### 3.3 Procedure of the Proposed Axial-Decoupled Method

The procedure of the proposed axial-decoupled positioning method can be presented as follows:

- I.** Firstly, partitioning ROI into a grid of cells, then collecting RSS data in each cell and decomposing into X- and Y-axis training samples. Lastly, determining the X- and Y-position according to decomposed samples (in terms of Step 2–5), respectively.
- II. Preprocessing:** Normalizing the training samples to the  $[-1, 1]$ .
- III. Training phase:** (i) classifier parameters: when using LS-SVM, SVM, first select the parameters  $(c, g)$  by grid search method; (ii) train classifiers by One-Against-All (OAA) [27] or One-Against-One (OAO) [28] approach independently.

Axial-decoupled positioning technique classifies the fingerprint samples of X- and Y-axis with OAO or OAA independently to locate the target. One of the differences of OAO and OAA approaches lies in the required classifiers [27, 28]: as for  $k$  class problem,  $k(k-1)/2$  binary classifiers are needed for OAO approach; however, OAA approach requires  $k$  binary classifiers.

- IV. Online phase:** normalizing the test samples and obtaining the X- and Y-axis categories according to classifier results in the Step 3.
- V.** Calculating the positioning output according to IV.

### 3.4 Performance Analysis

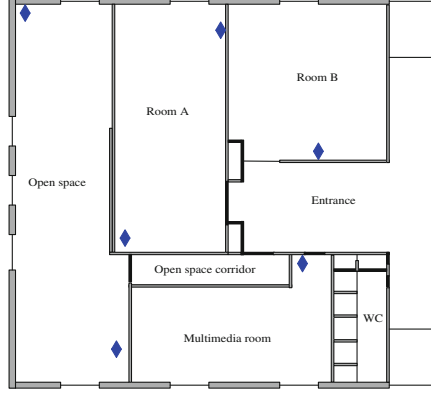
The common pattern classifier based fingerprint approach is to partition the ROI into a number of regions, each representing a class. Typically, grid partitioning is used, a unit cell of this partition is chosen as one class. If the 2D positioning area is portioned as  $l_x \times l_y$  grids, each being a cell of size  $1/l_x \times 1/l_y$ . Thus, there are  $l_x \cdot l_y$  classes. Using a multiclass classifier, a fingerprint can be classified into one of these classes and the center of the corresponding cell is the location estimate. It refers to grid method. However, rather than estimating both X- and Y-coordinate simultaneously, the proposed axial-decoupled method estimates the coordinates independently. For the X-axis, the area is partitioned into  $l_x$  column stripes, each serving as a class. Therefore there are  $l_x$  classes for the X-axis. Using a multiclass classifier, we can classify the X-coordinate into one of these stripes. Similarly, in a separate classification procedure,  $l_y$  classes are obtained by partitioning the area into row stripes and used to estimate the Y-coordinate. It can be seen from the above analysis, this method uses only  $l_x + l_y$  classes, which is much fewer than  $l_x \cdot l_y$  (commonly for multi-label classifier based indoor positioning,  $l_x, l_y \gg 1$ ). The corresponding training time is reduced because the number of classifier decreased.

## 4 Experiment and Discussion

### 4.1 Test Dataset and Model Parameter Selection

To evaluate the performance of our axial-decoupled positioning method, we conduct experiments using two benchmarks:

- (a) Small-size dataset: This dataset is from an indoor experiment used in [25] (University of Trento), containing a collection of 257 RSS fingerprints at 257 sample locations in a WLAN with 6 APs (Fig. 2). The sample locations are regular-grid points of the floor. Each fingerprint is measured at a sample location by a person carrying a personal digital assistant (PDA), as a receiver receiving signals from the APs. The PDA always points at north. A random 90 % of this collection (232 samples) is used for training and the rest of the samples (25 samples) are for testing.
- (b) Large-size dataset: This dataset is from a real-world large-scale RSS dataset (From Xiangtan University Building of College of Information Engineering). The ROI is a room with an area of  $14 \text{ m} \times 6 \text{ m}$ . In this room area, 84 partitioned grids of size  $1 \text{ m} \times 1 \text{ m}$  are used. A fully regular grid could not be followed due to the presence of various obstacles such as tables and other furniture. RSS fingerprints are collected from 84 grids in a WLAN with twelve APs. It should be pointed out that only 4 of APs' positions are given previously. Measurements on some grids are in NLOS condition due to the obstacles such as wall, desk and other devices while others are in LOS condition. For each grid, we collect 40 RSS measurements from all APs by a person carrying a PDA, and the PDA points at four different heading orientations (east/west/south/north). This results totally 3360



**Fig. 2.** The small-size dataset's map: 30 m  $\times$  25 m (after [25]); the blue diamond represents the position of the six access points

samples, from which we randomly use 90 % dataset as the training set (3024 samples) and the rest of the samples (336 samples) for testing.

The experimental operation environment is Windows XP operating system, CPU G645, 3.47G RAM, MATLAB R2009a. In order to compare the advantages of the axial-decoupled indoor positioning method to traditional indoor positioning method, pattern classifiers like LS-SVM, SVM, and K-NN are applied to location fingerprint positioning framework. When using LS-SVM and SVM, we need to choose kernel function of the condition to satisfy Mercer [29]. There are a variety of kernel functions such as polynomial functions, radial basis functions (RBF) and sigmoid kernel. We take RBF as kernel function in the all experiments. Before the application of LS-SVM and SVM classification, the regularization and kernel parameter ( $c, g$ ) should be determined. Regularization parameter  $c$  affects the generalization ability of the classifier by controlling the misclassification rate. Parameter  $c$ , which is too high, will cause the fact that the accuracy of training set classification is too high while the accuracy of test set classification is too low. Parameter  $g$  determines the complexity of sample feature subspace distribution. Therefore, the parameter  $c$  and  $g$  jointly influence classifier generalization ability and the final location accuracy. In this section, the apartments are determined through grid searching from  $[2^{-10}, 2^{10}]$ . For K-NN,  $K$  (e.g., 1, 3 or 5) represents the number of nearest-neighbor fingerprints used to estimate the unknown location, while distance-type can be "E" and "M" that presents Euclidean distance and Manhattan distance, respectively.

For ease of presentation, classifiers under axial-decoupled framework are denoted as AD-LS-SVM, AD-SVM, AD-1NN(E), AD-1NN(M), AD-3NN(E), AD-3NN(M), AD-5NN(E), AD-5NN(M), respectively.

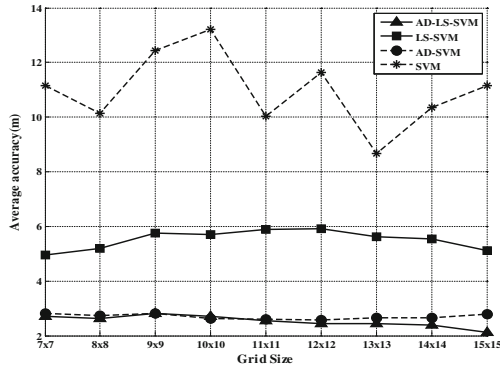
## 4.2 Results and Discussion

### A. Small-size Dataset

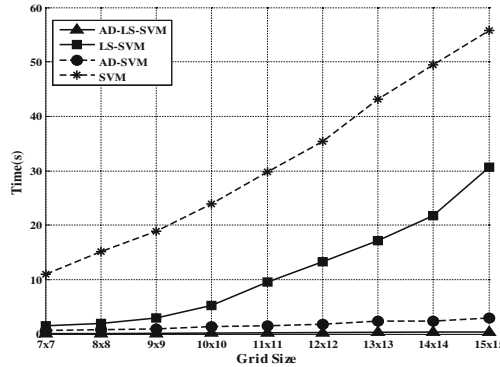
In the small-size dataset experiment, the grid size parameter is  $l_x \times l_y \in \{7 \times 7, 8 \times 8, \dots, 15 \times 15\}$ . To compare the proposed method with traditional method, we use LS-SVM, SVM and K-NN classifier for the positioning of axial-decoupled or traditional grid method. Figure 3 is the experimental result (various cases of LS-SVM and SVM adopts OAO combination approach) of LS-SVM and SVM classifier under the condition of decoupled and non-decoupled in the different grid size.

From Fig. 3, we can see that the following conclusions:

- (i) Decoupled vs. Non-decoupled: For LS-SVM and SVM, location accuracy and computation time of the decoupled are obviously better than the non-decoupled. In terms of location accuracy, the grid size shows slightly influence on decoupled positioning method. With the successive increase of grid density, location



(a) Location accuracy



(b) Time complexity

**Fig. 3.** Location accuracy and time complexity of different methods



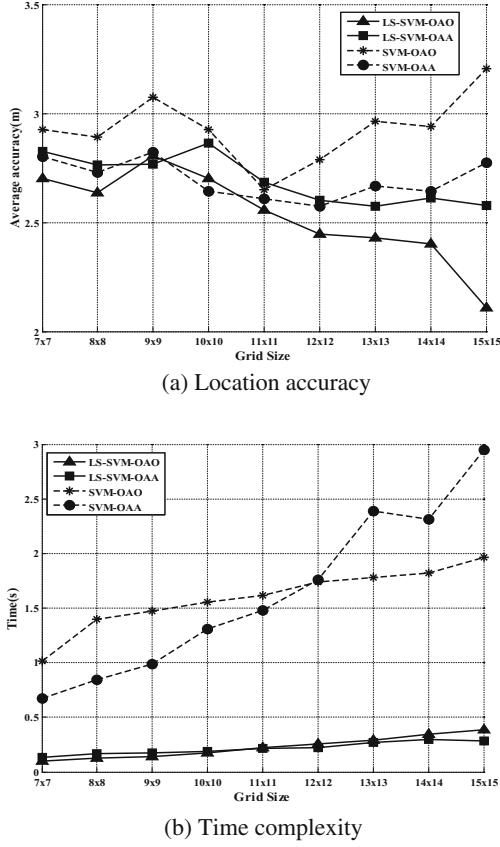
accuracy changes in positioning method based on decoupled classifier relatively tends to be slow, while the change of the non-decoupled classifier is much more severe. As we can see from Fig. 3(a), When the grid size is  $15 \times 15$ , AD-LS-SVM will get a relatively good location accuracy (2.1071 m), it is a half of LS-SVM (5.1051 m). When it comes to computational costs, the time needed for decoupled classifier is far less than non-decoupled classifier. As the grid density increased, time needed for two kinds of classification methods is also increased accordingly. But the growing speed in non-decoupled is much faster than the decoupled positioning technique proposed in this paper. It is observed from Fig. 3(b), the time of LS-SVM (30.62 s) needed is 80 times longer than that of AD-LS-SVM (0.38 s) in the grid size of  $15 \times 15$ . Therefore, the location fingerprint positioning method of axial-decoupled has higher location accuracy and a lower computational cost than non-decoupled.

- (ii) LS-SVM vs. SVM: In non-decoupled, LS-SVM and SVM differ largely both in location accuracy and computation time. When concerning location accuracy, LS-SVM is higher than SVM, the location error of which is almost twice than that of the former. As the increase of grid density, LS-SVM location accuracy is relatively stable, while the SVM is volatile. In terms of computation time, LS-SVM under the same grid is much lower than SVM, the cost of which is almost twice to three times than that of the former. It is observed that the time of SVM method increase faster when the grid becomes denser, the time of SVM is even longer than that of LS-SVM. Because the number of classes in each method increases with the grid becomes denser. Therefore, LS-SVM has both a better positioning effect and a lower time complexity than SVM in non-decoupled.
- (iii) AD-LS-SVM vs. AD-SVM: For the evaluation, the AD-LS-SVM is comparable to AD-SVM both in location accuracy and computation time. When the grid becomes larger, the location accuracy of AD-SVM is slightly higher than AD-LS-SVM. In the case  $(l_x, l_y) = (10, 10)$ , where the location accuracy remains the same. With the grid density increased, not only the location accuracy of AD-LS-SVM is slightly better than AD-SVM but also the computation time needed for AD-LS-SVM in any grid density is less than AD-SVM.

In order to further analyze the decoupled positioning technique. Figure 4 shows the average location accuracy and time complexity varying with the grid density. Here we adopt OAO and OAA approach for AD-LS-SVM and AD-SVM classifier.

From Fig. 4, we can see that the following conclusions:

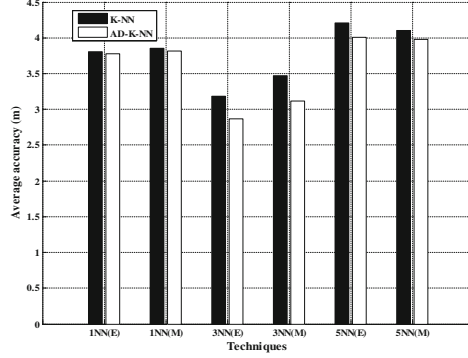
- (i) Location accuracy of OAO and OAA: For a specific classifier (e.g., LS-SVM or SVM), positioning accuracy of the classifier based on OAO approach is slightly higher than that of OAA approach. With the increase of grid density, the positioning accuracy changes of OAO and OAA is similar, in other words, the location accuracy is worse with the grid density increased. But when the grid density reaches a certain value (e.g.,  $11 \times 11$  for AD-SVM-OAA,  $12 \times 12$  for AD-SVM-OAO), the location accuracy becomes rather poor (except AD-LS-SVM-OAO).



**Fig. 4.** AD-LS-SVM, AD-SVM: OAO vs. OAA

- (ii) Computational complexity of OAO and OAA: For LS-SVM, we can see that the time of OAO approach increases faster when the grid becomes denser, especially when the grid increases to a certain extent (e.g.,  $11 \times 11$  or  $12 \times 12$ ) or more, the time of OAO is even longer than that of OAA. Because classification function increases with classes, and lower its speed in the decision-making process. Similarly, the same conclusions can be obtained as for SVM.

From the above analysis, we can see that the positioning precision of OAO approach is superior to OAA for a specific classifier. The computation time has relationship with the size and class of training samples. When the grid density is small, the computation time is lower than that of OAA. When the grid density is increased to a certain extent, costs of the former will surpass the latter, and both computational costs are increasing. Figure 5 shows the average location accuracy of K-NN classifier in decoupled and non-decoupled conditions when the grid parameter is  $7 \times 7$ .



**Fig. 5.** K-NN's location accuracy varying with different  $K$  under decoupled and non-decoupled conditions

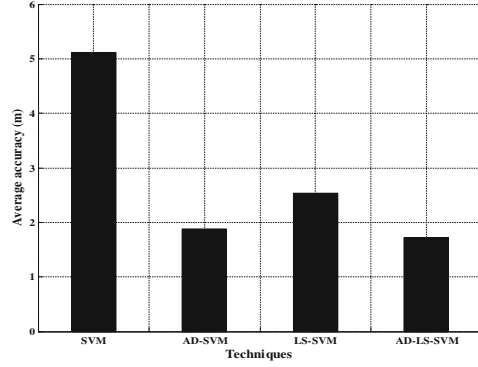
From Fig. 5, it is clearly see that the location accuracy of decoupled K-NNs is superior to non-decoupled ones, but both of them are worse than AD-LS-SVM and AD-SVM. Furthermore, the number of neighbors also affects the performance of technique and the value of  $K$  must be chosen carefully. When  $K = 3$ , the location accuracy is commonly superior to  $K = 1$  and  $K = 5$ , whether using Euclidean distance or Manhattan distance. In addition, we can see that the precision is higher in using Euclidean distance when  $K = 3$ . It is because that taking only one neighbor into consideration may obtain a good accuracy but poor robustness. On the other hand, considering too many neighbors, even if it limits the risk of *wrong* neighbor, widens the potential area for the estimate location and thus leads to a lower accuracy.

### B. Large-size Dataset

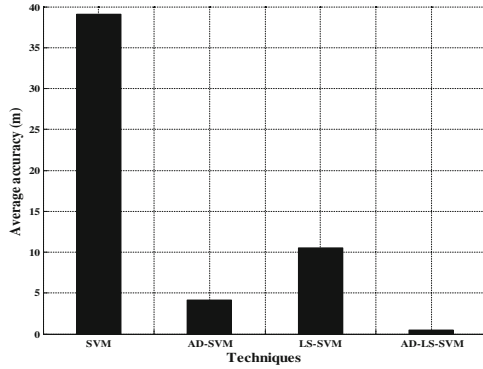
To show how our algorithm is also suitable for large-size dataset, the following experiment is made. In the large-size dataset experiment, the grid size parameter is  $l_x \times l_y = 14 \times 6$ . When comparing the proposed method with traditional method, we also use LS-SVM, SVM and K-NN classifier for the positioning of axial-decoupled and traditional grid method. Figure 6 is the experimental result (various cases of LS-SVM and SVM adopts OAO combination approach) of LS-SVM and SVM classifier under the condition of decoupled and non-decoupled.

Figure 6 shows the average localization accuracy and time complexity varying in decoupled and non-decoupled conditions. As noticed, the location accuracy and computation time of proposed decoupled method are obviously better than traditional grid method. Comparing four methods in the Fig. 6, we observe that AD-LS-SVM is the one with the best location accuracy (1.7217 m) and the lowest computational burden (0.4649 s), while SVM is the contrary. As we can see from Fig. 6, it's obvious that LS-SVM has a better location accuracy and the lowest time compared with the SVM. This experiment strongly indicates that, for the large-size dataset, our proposed method is substantially better than traditional grid methods.

Figure 7 shows the average location accuracy of K-NN classifier in decoupled and non-decoupled when the grid parameter is  $14 \times 6$ . From Fig. 7, we can clearly see that the



(a) Location accuracy



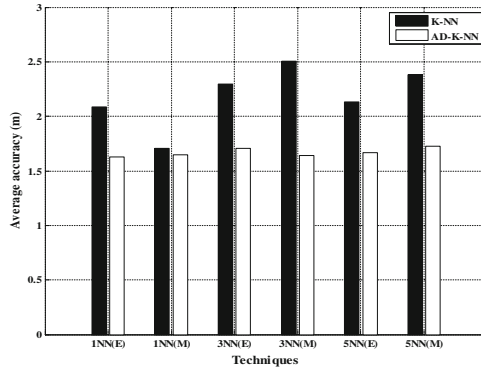
(b) Time Complexity

**Fig. 6.** Location accuracy and time complexity of different methods

location accuracy of decoupled K-NNs is superior to non-decoupled ones. Both can obtain similar accuracy with decoupled LS-SVM and decoupled SVM. It is observed that the Euclidean distance and Manhattan distance provide similar results. In addition, the number of neighbors also affects the performance of technique and the value of  $K$  must be chosen carefully. Figure 7 shows that for K-NNs a smaller  $K$  corresponding to better location accuracy. The best location accuracy (1.6288 m) is achieved by 1NN(E).

### C. Remarks

Our experiment with the small and large datasets has shown that: (1) axial-decoupled method is much better than traditional grid method, both in location accuracy and computation complexity; (2) AD-LS-SVM and AD-SVM are comparable with each other, the former is slightly more accurate and faster; (3) Among the traditional grid methods, LS-SVM is obvious better than SVM and with the best location accuracy and the lowest computational burden; (4) LS-SVM and SVM are substantially less accurate than K-NN in the traditional grid methods; (5) The location accuracy of OAO approach is superior to OAA for a specific classifier.



**Fig. 7.** K-NN's location accuracy varying with different  $K$  under decoupled and non-decoupled conditions

## 5 Conclusion and Future Work

Axial-decoupled indoor positioning based on location fingerprints is proposed. The experiment results of traditional methods such as LS-SVM, SVM and K-NN show that axial-decoupled ones are much better than traditional grid ones, both in location accuracy and computation complexity. In the near future, we would focus on studying the feature selection of RSS and the dynamic target tracking that based on the axial-decoupled indoor positioning.

**Acknowledgements.** This work is supported by the National Natural Science Foundation of China (No. 61100140 and 61104210).

## References

1. Serthth, C., Fujii, T., Ohtsuki, T.: Multi-band received signal strength fingerprinting based indoor location system. *IEICE Trans. Commun.* **93**(8), 1993–2003 (2010)
2. Akyildiz, I.F., Su, W., Sankarasubramaniam, Y., Cayirci, E.: A survey on sensor networks. *IEEE Commun. Mag.* **40**(8), 102–114 (2002)
3. Popov, L.: iNav: a hybrid approach to Wi-Fi localization and tracking of mobile devices. In: Samuel, M. (ed.) *Computer Science and Engineering*, pp. 59–60. MIT, Massachusetts (2008)
4. Chiang, S.Y., Kan, Y.C., Lin, H.C.: Precise RSSI models for practical indoor WSN localization. *Inf. Int. Interdisc. J.* **16**(12), 8869–8885 (2013)
5. Feng, C., Au, W.S.A., Valaee, S.: Received-signal-strength-based indoor positioning using compressive sensing. *IEEE Trans. Mob. Comput.* **11**(12), 1983–1993 (2012)
6. Genming, D., Zhenhui, T.A.N., Jinsong, W.U.: Efficient indoor fingerprinting localization technique using regional propagation model. *IEICE Trans. Commun.* **97**(8), 1728–1741 (2014)
7. Hwang, J., Yoe, H.: Design and implementation of the Livestock activity monitoring system using RSSI of ZigBee and ratiometric. *Inf. Int. Interdisc. J.* **17**(3), 1047–1052 (2014)

8. Paul, A.S., Wan, E.A.: Wi-Fi based indoor localization and tracking using sigma-point Kalman filtering methods. In: *Proceedings of the IEEE/ION Symposium on Position, Location & Navigation*, pp. 646–659, May 2008
9. Goldsmith, A.: *Wireless Communications*. Cambridge University Press, New York (2005)
10. Kaemarungsi, K., Krishnamurthy, P.: Modeling of indoor positioning systems based on location fingerprinting. In: *Proceedings of the 23th IEEE Computer and Communications Societies*, vol. 2, pp. 1012–1022, March 2004
11. Bahl, P., Padmanabhan, V.N.: RADAR: an in-building RF-based user location and tracking system. In: *Proceedings of the 19th IEEE Annual Joint Conference on Computer and Communications Societies*, vol. 2, pp. 775–784, March 2000
12. Yang, Q., Pan, S.J., Zheng, V.W.: Estimating location using wi-fi. *IEEE Intell. Syst.* **23**(1), 8–13 (2008)
13. Ahriz, I., Oussar, Y., Denby, B.: Full-band GSM fingerprints for indoor localization using a machine learning approach. *Int. J. Navig. Obs.* **2010**(2010), 7 (2010)
14. Kjærgaard, M.B.: A taxonomy for radio location fingerprinting. In: Hightower, J., Schiele, B., Strang, T. (eds.) *LoCA 2007*. LNCS, vol. 4718, pp. 139–156. Springer, Heidelberg (2007)
15. Genming, D., Zhenhuim, T.A.N., Jinsong, W.U.: Indoor Fingerprinting Localization and Tracking System Using Particle Swarm Optimization and Kalman Filter. *IEICE Trans. Communications* **98**(3), 502–514 (2015)
16. Mautz, R.: Overview of current indoor positioning systems. *Geodezija ir Kartografija* **35**(1), 18–22 (2009)
17. Figuera, C., Rojo-Álvarez, J.L., Wilby, M.: Advanced support vector machines for 802.11 indoor location. *Sig. Process.* **92**(9), 2126–2136 (2012)
18. Zhu, Y.J., Deng, Z.L.: Multi-classification algorithm for indoor positioning based on support vector machine. *Comput. Sci.* **39**(4), 32–35 (2012)
19. Shin, J., Han, D.: Multi-classifier for WLAN fingerprint-based positioning system. In: *Proceedings of World Congress on Engineering 2010*, London, UK, vol. 1, June 2010
20. Xu, L., Krzyzak, A., Suen, C.Y.: Methods of combining multiple classifiers and their applications to handwriting recognition. *IEEE Trans. Syst. Man Cybern.* **22**(3), 418–435 (1992)
21. Kuncheva, L.I., Bezdek, J.C., Duin, R.P.W.: Decision templates for multiple classifier fusion: an experimental comparison. *Pattern Recogn.* **34**(2), 299–314 (2001)
22. Xiang, L., Wang, D., Wei, Y.H.: Location-fingerprint based indoor localization via scalable semi-supervised learning. *Information-An Int. Interdisc. J.* **18**(2), 641–652 (2015)
23. Dortz, N.L., Gain, F., Zetterberg, P.: Wi-Fi fingerprint indoor positioning system using probability distribution comparison. In: *Proceedings IEEE Acoustics, Speech and Signal Processing*, pp. 2301–2304 (2012)
24. Duda, R.O. (ed.): *Pattern Classification*. Wiley, Hoboken (2012)
25. Battiti, R., Brunato, M.: Statistical learning theory for location fingerprinting in wireless LANs. *Comput. Netw.* **47**(6), 825–845 (2005)
26. Tagashira, S., Kanekiyo, Y., Arakawa, Y., et al.: Collaborative filtering for position estimation error correction in WLAN positioning systems. *IEICE Trans. Commun.* **94**(3), 649–657 (2011)
27. Anand, R., Mehrotra, K., Mohan, C.K.: Efficient classification for multiclass problems using modular neural networks. *IEEE Trans. Neural Netw.* **6**(1), 117–124 (1995)
28. Hastie, T., Tibshirani, R.: Classification by pairwise coupling. *Ann. Stat.* **26**(2), 451–471 (1998)
29. Sun, Z., Sun, Y.: Fuzzy support vector machine for regression. *IEEE Trans. Fuzzy Syst.* **4**(2), 3336–3341 (2003)

Pattern Recognition

7th Chinese Conference, CCPR 2016, Chengdu, China,

November 5-7, 2016, Proceedings, Part I

Tan, T.; Li, X.; Chen, X.; Zhou, J.; Yang, J.; Cheng, H.

(Eds.)

2016, XXIII, 783 p. 339 illus., Softcover

ISBN: 978-981-10-3001-7