INBS: An Improved Naive Bayes Simple Learning Approach for Accurate Indoor Localization

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***Abstract*—Indoor localization based on WiFi signal strength fingerprinting techniques have been attracting many research efforts in past decades. Many localization algorithms have been proposed in order to achieve higher localization accuracy. In this paper, we investigate Bayes learning algorithms and some common-used machine learning algorithms. We identify a general problem of Zero Probability (ZP) which may cause significant decrease of accuracy. In order to solve this problem, we propose an Improved Naive Bayes Simple learning algorithm, namely INBS, based on our data set characteristic. INBS is applicable even though Zero Probability problem occurs. We design experiments based on off-the-shelf WiFi devices, mobile phones and well-known machine learning tool Weka. Our experiments are conducted on a floor covering $560m^2$ in a campus building and a laboratory covering $78m^2$. Experiment results show that INBS outperforms traditional Naive Bayes and k-Nearest Neighbors (k-NN) algorithms and two common-used machine learning algorithms in terms of accuracy.**

I. Introduction

Locating wireless client in indoor spaces, which are beyond GPS coverage, is an important task in many applications that range from context-aware computing, location-based services. With the growing popularity of mobile and pervasive computing, many research and commercial systems on wireless indoor localization have been developed in the past decades. Most of the solutions are introduced to provide room-level location-based service, for example, locating a person equipped some sensors like mobile phones or some asserts like desktop computers in an office building [13], [14], [15], [16].

The majority of previous location approaches utilize Received Signal Strength (RSS), known as fingerprinting [4], as a metric for indoor location determinations. These localization approaches are based on the fact that each point in the space has a unique fingerprint of signal parameters. These approaches are usually divided into two phases: offline and online phases. The first phase, which is also referred to as training or calibration phase, involves a site survey process, in which the RSS fingerprints (e.g., WiFi signal strengths from multiple Access Points, APs) at every location of an interested area are collected by the mobile device and accordingly built into a fingerprint database (*a.k.a.* radio map). During the online phase, both deterministic and probabilistic methods can be employed as localization algorithms. The deterministic method chooses the reference point in the database whose signal strength has the minimum difference from the RSS of the device as location [4]; while the probabilistic one chooses the most likely location of the device in database as the most probable location [9], [7] .

A classification algorithm usually is the core part of indoor localization, since most of time the accuracy and training cost is varied with different algorithms. k-NN algorithm [4], [5] and many machine learning methods, such as Gaussian Processes [1], [2], Bayes learning [3], are widely used as the classification methods. In this paper, we investigate some common-used classification algorithms. When collecting data, we discover that RSS is conditional independent, which is a basic prerequisite of applying Bayes learning, so we believe Bayes learning will get good performance. However, Zero Probability (ZP) caused by data incompleteness could significantly decrease the localization accuracy (Fig. 1). Based on this problem and our data characteristics, we make some improvement of the Naive Bayes learning algorithm.

The contributions of this paper are three-fold: i) we design and implement an Improved Naive Bayes Simple algorithm, called INBS, which can cope with the Zero Probability problem; ii) we conduct extensive experiments on the testbed of off-the-shelf WiFi devices and mobile phones; iii) we compare INBS with traditional Naive Bayes, k-NN and two other machine learning algorithms and show that INBS outperforms these algorithms in terms of accuracy.

This paper is organized as follows. The section that follows provides a critical review of the ongoing research. Section III presents an overview of the theory behind the Bayes learning and introduces the Improved Naive Bayes Simple learning algorithm. Section IV presents experiment scenarios and the performance comparisons of different localization algorithms. Finally, section V concludes this paper and suggests directions for future research.

II. RELATED WORK

The location estimation using WiFi fingerprint often refers to the machine learning issue because accuracy of the location estimation depends on the use of classifiers. For this reason,

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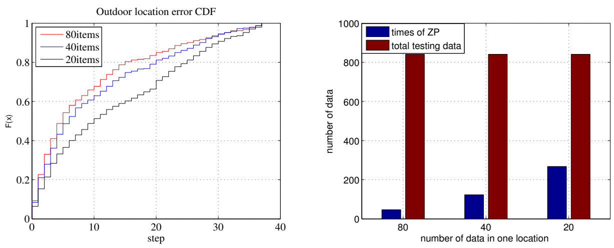


(a) (b)

Fig. 1: Zero probability problem.

various classification methods have been proposed, which can be divided into two classes: deterministic and probabilistic techniques.

Deterministic systems compute the location estimate as a function of the measured RSS values using a physical model incorporating the values stored in the fingerprint database. k-NN [1] [4] is one of the simplest classification methods widely used in fingerprinting-based localization system. But one drawback of it is that it needs to determine an optimal value of k to get an accurate estimate.

On the other hand probabilistic techniques compute a distribution based on the measurements from the offline phase and use probabilistic techniques to estimate the user's position. A. Matic *et al.* [1] and A. Bekkali *et al.* [2] choose Gaussian Process (GP) regression to estimate the localization accuracy. M. Kessel *et al.* [11] and J. Ledlie *et al.* [12] use Naive Bayes as the classification algorithm in their systems, of which the former uses the algorithm to investigate reduction influence caused by user orientation and the latter induces a new statistical algorithm based on Naive Bayes Algorithm.

In this paper, we investigate the effect of Naive Bayes (NB) Algorithm on indoor localization, because it is easy to conduct and we believe that the RSS data is conditional independent (Fig. 4). But a general problem of zero conditional probability may reduce the performance of NB. Based on this problem and our data set characteristic, we propose an improved Naive Bayes learning algorithm and compare the performance with some common-used localization algorithms.

III. IMPROVED LOCALIZATION ALGORITHM BASED ON NAIVE BAYES

Given a set of objects, each of which belongs to a known class and has known vector of variables, our aim is to construct a rule that will allow us to assign future objects to a class, given only the vectors variables describing the future objects. Indoor localization belongs to this kind of problem. The purpose of Indoor localization is to model the dependence of the RF signal strength with a spatial location. Thus, to implement a rule $\mathbf{R}^L \to \mathbf{R}$, that relates the measured RSS vector from L APs to a spatial location and RSS measurements, is highly nonlinear due to several parameters such as multipath, fading, NLOS and interference from other devices. This scenario leads to a complex spatial distribution of the RSS and can not be described by simple parametrical models.

This kind of problems, called problems of *supervised classification*, are ubiquitous, and many methods for constructing such rules have been developed. One very important method is the *naive Bayes* method, also called *simple Bayes*, or *independence Bayes*. In view of the training location paired with observed RSS output, we try to create a function that summarizes input-output relationship on the basis of the Bayes supervised learning machine. In fact, the idea is to apply Bayes learning technique for prediction of RSS data in the room, using the available RSS training data to infer the target location.

A. Learning Classifiers based on Bayes Rule

Let $X = \{X_i, i = 1, \ldots, N\}$ be a set of observed RSS data and $Y = \{Y_i, i = 1, \ldots, N\}$ be the corresponding coordinate points so that the pair (X_i, Y_i) represents the training data. This is a supervised learning problem in which we wish to approximate an unknown target function $f : X \to Y$, or equivalently $P(Y|X)$.

Applying Bayes rule, we see that $P(Y = y_i|X)$ can be represented as

$$P(Y=y_i|X=x_k)=\frac{P(X=x_k|Y=y_i)P(Y=y_i)}{\sum_j P(X=x_k|Y=y_j)P(Y=y_j)}, \quad (1)$$

where y_i denotes the i-th possible value for Y, x_k denotes the k-th possible vector value for X, and where the summation in the denominator is over all values of the random variable Y.

We can get $P(Y|X)$ by using the training data to estimate $P(X|Y)$ and $P(Y)$. Then $P(Y|X = x_k)$ can be calculated by these estimates and above-mentioned Bayes rules for any new instance x_k.

When we are going to train a Bayes classifier by estimating $P(X|Y)$ and $P(Y)$, it is necessary to know how much training data will be required to obtain reliable estimates of these distributions. Typically, an order of hundred of training data is sufficient to obtain maximum likelihood estimation of $P(Y)$ when Y is a boolean variable. However, accurately estimating $P(X|Y)$ typically requires many more examples.

Conditional Independence Given random variables X, Y and Z, X is conditionally independent of Y given Z, if and only if Z occurs, knowledge of whether X occurs provides no information on the likelihood of Y occurring, and knowledge of whether Y occurs provides no information on the likelihood of X , that is

$$(\forall i,j,k)P(X=x_i|Y=y_j,Z=z_k)=P(X=x_i|Z=z_k). \quad (2)$$

We believe that the data we collected in our experiment satisfies this condition, because ideally one point is supposed to correspond to three fixed RSSs. Though there are certain fluctuation in actual environment (Fig. 4), they are independent each other.

B. Improved Localization Algorithm Based on Naive Bayes

The Improved Naive Bayes algorithm is a classification algorithm based on Bayes rule. The location can be calculated as the followed steps. Assumes the attributes $X_1, \ldots, X_n$ are the Received Signal Strength (RSS) and they are all conditionally independent of each other. Let Y be the set of all locations. The value of this assumption is that it dramatically simplifies the representation of $P(X|Y)$, and the problem of estimating it from the training data. According to the property of probabilities and the definition of conditional independence, we have

$$\begin{aligned} P(X_1, \ldots, X_n|Y) &= P(X_i, \ldots, X_{n-1}|X_n, Y)P(X_n|Y) \\ &= \textstyle\prod_{i=1}^{n} P(X_i|Y). \end{aligned} \tag{3}$$

Assuming that Y is any discrete-value variable, and the attributes $X_1, \ldots, X_n$ are any discrete or real-valued attributes. Our goal is to train a classifier that will output the probability distribution over possible values of Y, for each new instance X that need to be classified. The expression for the probability that Y will take on its k-th possible value, according to Bayes rule, is

$$P(Y = y_k|X_1, \ldots, X_n) = \frac{P(Y{=}y_k)P(X_1,\ldots,X_n|Y{=}y_k)}{\sum_j P(Y{=}y_j)P(X_1,\ldots,X_n|Y{=}y_j)} \tag{4}$$

where the sum is taken over all possible values y_j of Y. Now, assuming the X_i is conditionally independent of given Y, Equation (4) can be rewritten as

$$P(Y = y_k|X_1, \ldots, X_n) = \frac{P(Y{=}y_k)\prod_i P(X_i|Y{=}y_k)}{\sum_j P(Y{=}y_j)\prod_i P(X_i|Y{=}y_j)} \tag{5}$$

Equation (5) is the fundamental equation for the Naive Bayes classifier. Given a new instance $X^{new} = \langle X_1, \ldots, X_n \rangle$, this equation shows how to calculate the probability that Y will take on any given value, the observed attribute values of X^{new} and the distributions $P(Y)$ and $P(X|Y)$ estimated from the training data. If we are interested only in the most probable value of Y, then we have the Naive Bayes classification rule:

$$Y \leftarrow \max_{y_k} \frac{P(Y = y_k)\prod_i P(X_i|Y = y_k)}{\sum_j P(Y = y_j)\prod_i P(X_i|Y = y_j)}, \tag{6}$$

which simplifies to the following (because the denominator does not depend on y_k)

$$Y \leftarrow \max_{y_k} P(Y = y_k) \prod_i P(X_i|Y = y_k). \tag{7}$$

Bayes learning algorithm performs well when using huge database. However, there is a problem when applying Equation (7). Once the user instance's attribute contains a new feature item, like $X' \notin X_i$, it will result in **zero conditional probability problem**, no matter how high the other feature items' conditional probabilities are. In Equation (7), $P(X_i|Y = y_k)$ equals to 0, when the value of X_i does not appear in the attribute X_i of the class y_k. This always leads to a bad result.

The zero conditional probability directly ignores the role of other attributes. We believe that even though new feature items don't occur, they still provides some useful information. So based on our data set, we propose an Improved Naive Bayes learning algorithm to solve the problem. Algorithm 1 shows the pseudocode.

The algorithm is still divided by two phrases: *training* and *test*. In the training phrase, we calculation the conditional probability distribution, $distri$, of attribute j's value in our training instance to its corresponding class and its probability distribution $classdistri$.

$$P(a_i|Y{=}y_k) = \begin{cases} P(a_i|y_k) & \text{if } P(a_i|y_k) \neq 0; \\ maxP(a_i'|y_k) \times (1 - \frac{abs(a_j'-a_j)}{abs(a_j'+a_j)})^{\omega} & \text{if } P(a_i|y_k) = 0. \end{cases} \tag{8}$$

In the test phrase, we modify the method of calculating $P(a_i|Y{=}y_k)$ as Equation (8). We first store each class's distribution to $prob[k]$. Then given a test instance, if the value of attribute j exists in the same attribute of training data set of class k, we get the conditional probability of this value to class k, and then we multiply the conditional probability to $prob[k]$. If the value of attribute j does not exist in the same attribute of training data set of class k, we first find a nearest value a_j' of class k to attribute a_j in training data. Then we calculate a weight ω by a_j' and a_j. At last, $prob[k]$ is multiplied by the conditional probability of a_j' and ω. After all the iterations, we compare the $prob[k]$, and return k as the predicted location if $prob[k]$ is the maximum in the probabilities of each class. The pseudocode is shown as Algorithm 1.

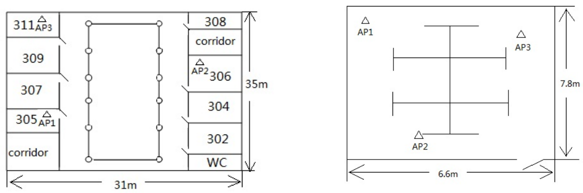
Algorithm 1 Improved Indoor Localization Algorithm Based on Naive Bayes

Input:
$train \leftarrow (a_1, a_2, \ldots, a_j, y_k)$;
$test \leftarrow (a_1', a_2', \ldots, a_i')$,
$j \in (0, \ldots, numAp), k \in (0, \ldots, numClass)$;
Output:
Predicted location k
Begin:
while $i \leftarrow 0, \ldots, n$ **do**
  $x \leftarrow train(i)$;
  while $j \leftarrow 0, \ldots, m$ **do**
    $distri[x[j]][x.class] \leftarrow p(x[j]|x.class)$;
  end while
  $classdistri[x.class] \leftarrow p(x.class)$;
end while

$x' \leftarrow test$;
while $k \leftarrow 0, \ldots, numClass$ **do**
  $prob[k] \leftarrow classdistri[k]$;
  while $j \leftarrow 0, \ldots, m$ **do**
    if $x_j' \in train[j][k]$ **then**
      $prob[k] \leftarrow prob[k] *$
      $distri[j][k].getprob(x'.value(j))$;
    else
      $a_j \leftarrow a_j' \quad if\ a_j'\ is\ nearest\ to\ a_j,$
      $a_j' \in train[j][k]$;
      $\omega \leftarrow \frac{a_j+a_j'-|a_j-a_j'|}{a_j+a_j'}$;
      $prob[k] \leftarrow prob[k] *$
      $distri[j][k].getprob(x'.value(j))^{\omega}$;
    end if
  end while
end while
return $predict \leftarrow k,\ if\ prob[k]\ is\ the$
$max\ \{prob[1],\ prob[2],\ \ldots,\ prob[m]\}$;

(a) (b)

Fig. 2: Experiment scenarios: (a) campus building floor, (b) a laboratory.



(a) (b)

Fig. 3: Simple structure of experiment scenarios in Figure 1 correspondingly.

IV. Evaluation

A. Experiment Design

In order to verify and analyze the efficiency of the Bayes algorithm, and its positioning accuracy, we use the increasingly popular Android OS, which supports scanning WiFi and is embedded with accelerator sensor, to collect RSS information and location information correspondingly in two indoor scenarios. Fig. 2 (a) shows a typical campus building floor, with the area of $31m \times 35m$, and Fig. 2 (b) shows a laboratory on the same floor, with the area of $6.6m \times 7.8m$.

Fig. 3 shows the simple structure of experiment scenarios and where we place 3 APs. The circles in Fig. 3 (a) are some pillars. The floor of our experiment scenarios are divided by many grids ($0.6m \times 0.6m$ for one grid). We sample the experiment area every two grids as a step. In the experiment, three Access Points are deployed, but we need not know the exactly locations of them, and two volunteers are needed to collect the WiFi signal strengths from the three Access Points and record the corresponding locations. The data is sent back every 2000 milliseconds and the total number of the pairs of RSS and locations sample are 7130. Finally, another volunteer conducts the location query by just sending back the collected WiFi signal strength, then the server calculates the predicted location by predefined classification algorithm and sends back to user.

Localization systems based on IEEE 802.11 wireless network always suffers from the fluctuations due to various factors, such as multi-path and shadow fading effects, which can cause the degradation of the positioning accuracy [8]. In order to get a high accuracy, we should try to ensure the wireless environment in our experiment is stable. We measured the wireless signal strength fluctuations at different times (Fig. 4). And we found that the wireless signal strength is limited within a reasonable range, except some sudden and short jitters.

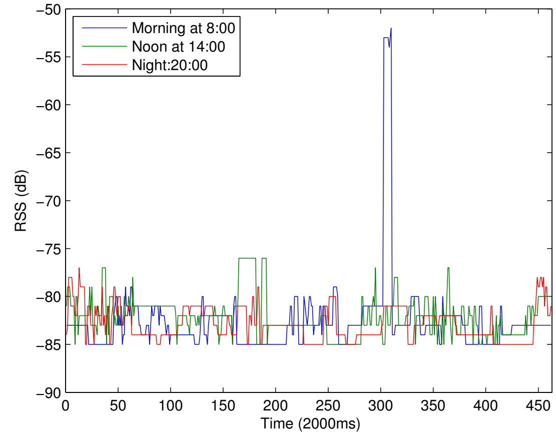


Fig. 4: RSS fluctuation of one location with different time.

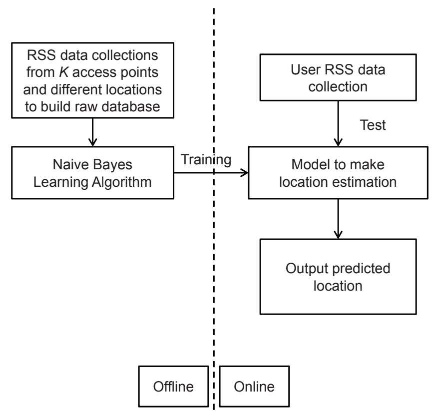


Fig. 5: The concept of Bayes learning based localization.

In this paper, probabilistic approach along with Bayes learning is adopted to infer the most likely location of the device in the training database as the most probable location. Fig. 5 shows the basic flow of the Bayes learning based indoor localization. In the off-line phase, the RSS data and location information from different APs are collected as raw data. Then, we apply the Naive Bayes learning algorithm to training the discrete observation data to build a model containing the probability distribution of RSS data at each location. In the online phase, the distributions of user's RSS data's in different locations are processed by Equation (5). Then the location whose distribution is satisfied with Equation (6) is chosen as the predicted location.

An important data processing tool we use in our experiment is Weka, Waikato Environment for Knowledge Analysis, which is a popular suite of machine learning software written in Java, developed at the University of Waikato, New Zealand. The Weka workbench contains a collection of visualization tools and algorithms for data analysis and predictive modeling,

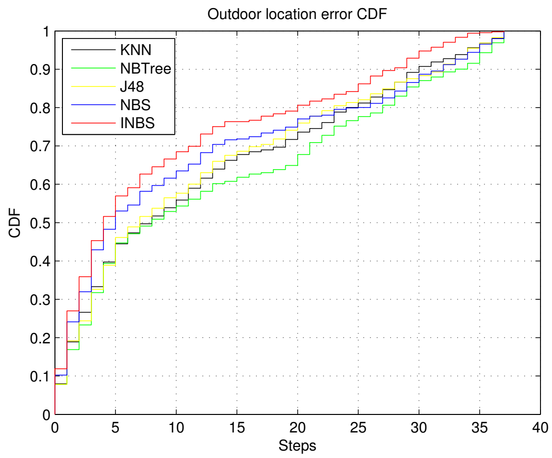


Fig. 6: CDF of location precision in the building floor.

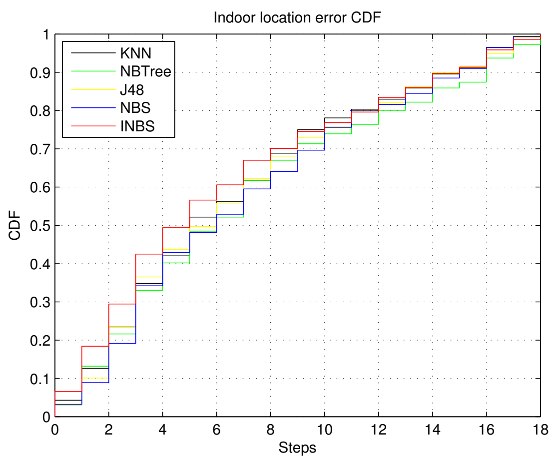


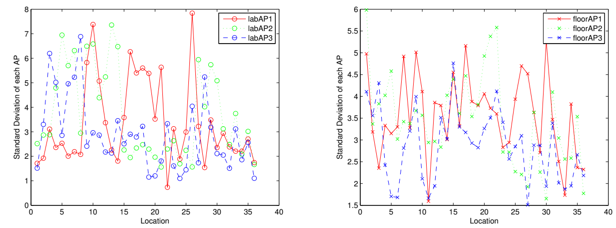
Fig. 7: CDF of location precision in the laboratory.

together with graphical user interfaces for easy access to this functionality. Weka supports several standard data mining tasks, more specifically, data preprocessing, clustering, classification, regression, visualization, and feature selection.

B. Performance Analysis

Fig. 6 and Fig. 7 show the CDF (Cumulative Distribution Function) of location error for the campus building floor and a laboratory respectively. In Fig. 6, we can see that the INBS (Improved Naive Bayes Simple) outperforms than other four algorithm, that is k-NN, J48, NBTree and Naive Bayes. The average localization error of INBS is $5.048m$, while the other four are $7.235m$, $7.079m$, $8m$ and $6.55m$.

Fig. 7 shows the result of applying these algorithms in a laboratory. It can clearly see that localization accuracy has been greatly improved, especially within 8 steps. We also find that the accuracy in the laboratory is higher than that of the building floor. We then calculate the standard deviation of each AP (Fig. 8). From the figure, we discover that, in generally, the standard deviations of APs in the laboratory are higher than the building floor. That means the RSS data collected in the laboratory is more easily to be classified since the



(a) Lab APs (b) Floor APs

Fig. 8: Standard deviations of each AP.

characteristic of each AP is more obvious. The reason is that there are some walls and pillars in the building floor, which mitigate the distinction degree of the building floor. However, the space in the laboratory is always in the line of sight and without many obstacles, as a result, the data is vulnerable and the data at one place is more easily to be discriminated from another place. Therefore, the data is more characterized and more easily classified. That is also clearly seen by Fig. 6 and Fig. 7, the location precision of the laboratory is about 75 percent when the location error is 10 steps, while the precision of the building floor is only almost 60 percent. As a result, these algorithms get similar results in laboratory.

V. Conclusions and Future Work

In this paper, the use of Naive Bayes for learning based indoor localization algorithm has been investigated. In order to solve the problem of Zero Probability, we propose the Improve Naive Bayes Simple learning algorithm based on our data characteristics. And the performance is compared in our study. Experiment results show that INBS outperforms traditional Naive Bayes and k-NN algorithms and two common-used machine learning algorithms in terms of accuracy. There is still much work that need to be done to get a more complete picture of location learning. The following lists some things that need to be investigated.

- Evaluate more learning algorithms including support vector machines and decision trees based learning algorithms. Examine ensemble estimators which use several algorithms to estimate location and then use the best combination to get highest performance.
- Explore some methods to reduce or harness the interference of many factors.
- Explore some methods to get comparable performance with lower calibration.

Acknowledgments

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