A Comparative Analysis of AI-assisted WiFi and BLE Indoor Positioning Systems

Yitong Wu

School of Electrical Engineering and Telecommunications, University of New South Wales, UNSW Sydney NSW 2052, Australia
yitong.wu1@student.unsw.edu.au

Abstract. Indoor positioning has become an on-going issue in recent years. Artificial Intelligence (AI), especially Machine Learning (ML) and Deep Learning (DL) algorithms assisted WiFi and Bluetooth Low Energy (BLE) fingerprinting indoor positioning systems are regarded as common techniques. This work conducts a comparative analysis of some of the state-of-the-art ML and DL algorithms that can be used to process fingerprinting data, as well as the trade-offs when applying them in different scenarios. This includes supervised and unsupervised machine learning models, and an innovative method combining Deep Neutral Network (DNN) and vector embedding. The result shows that vector embedding using i-vectors conducts the most accurate performance after model adaptation, supervised machine learning techniques like Support Vector Machine (SVM) can be regarded as a balance between accuracy and efficiency, unsupervised machine learning technique Density Based Spatial Clustering of Applications with Noise (DBSCAN) is more adaptable when there is much noise, but become less precise when there exists dynamic objects.

Keywords: Indoor positioning, Deep Learning, RSSI, Bluetooth Low Energy, WiFi.

1 Introduction

With the acceleration of urbanisation, people tend to spend more time indoors due to the trends in indoor working structures and the digital lifestyle. It is reported by the World Health Organisation (WHO) that modern people spend more than 80% of their time indoors. Thus, multi-layer indoor environments such as hospitals, airports and shopping centres cannot be neglected. However, people often struggle to get to their intended departments, boarding gates, or stores. Regular Global Navigation Satellite Systems such as Global Positioning System (GPS) used outdoors tend to perform imprecisely in these places due to signal blocking and attenuation [1]. Therefore, there is a rising demand for high-accuracy indoor positioning systems (IPSs) to be employed by indoor navigation systems. Such systems will contribute not only to regular scenarios when finding the way in unfamiliar places but also to emergency situations like earthquakes or fires to locate the injured [2].

S. Zhang (ed.), *Proceedings of the 2025 International Conference on Electronics, Electrical and Grid Technology (ICEEGT 2025)*, Advances in Engineering Research 292,
https://doi.org/10.2991/978-94-6463-986-5_51

Surveys based on multiple indoor positioning systems techniques, including Wireless Fidelity (WiFi) [3-5], Bluetooth Low Energy (BLE) Ultra-Wide Band (UWB) and Radio-Frequency Identification (RFID) have been conducted previously. WiFi and BLE techniques are considered the most widely used methods for two reasons [5-8]. Firstly, as Radio Frequency waves, they are universally accessible and flexible in complex indoor environments. Secondly, existing implementation methods such as fingerprinting simply use devices like smartphones with no need to build other platforms. Moreover, multiple advanced Artificial Intelligence (AI) algorithms like Machine Learning (ML) and Deep Learning (DL) also contribute to processing and analysing fingerprints [3, 4].

This work will investigate the difference between several common ML or DL approaches theoretically. This includes supervised and unsupervised machine learning models [9, 10], and an innovative method combining Deep Neutral Network (DNN) and vector embedding [11]. This research will also highlight the potential challenges and future optimisation directions based on the existing frames.

2 Method analysis

2.1 Supervised machine learning techniques

Two popular BLE fingerprinting algorithms are Heuristic Based Methods (HBM) and Received Signal Strength Indicator (RSSI) distance-based algorithms, each containing subcategories that deep learning models can be employed to [9]. The relationship between them is shown in Figure 1.

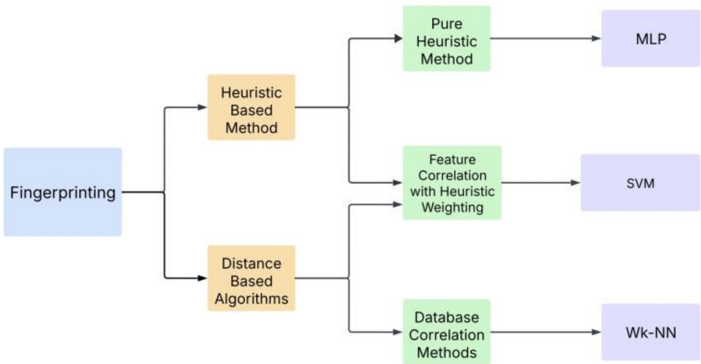

Figure. 1. BLE fingerprinting algorithms

Heuristic based methods. HBM are methods depending on heuristic algorithms that can be used to process an offline database in the fingerprinting procedure. Pure Heuristic Methods (PHM) and Feature Correlation with Heuristic Weighting (FCHW), which also belongs to the group of RSSI distance-based algorithms, are considered as its two subcategories. The most widely used solutions are Multi-Layer Perceptron (MLP) from the PHM subcategory, and SVM from the FCHW subcategory [9].

The structure of MLP is portrayed in Figure 2. It makes use of several completely connected layers, each with a different number of arranged perceptron. Each layer's elements calculate a weighted total of their inputs, which is subsequently scaled using an activation function. The output from each layer is then subsequently sent to the next layer to be processed, and in the end, the result is shown on the last layer perceptron [9].

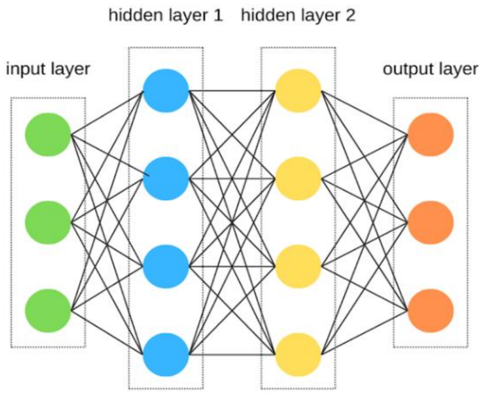

Figure. 2. MLP schematic diagram

Support vectors are specific distances calculated by SVM based on certain elements. These vectors are utilised to generate multiple hyperplanes that separate different data categories, as shown in Figure 3. SVM calculates the distance with respect to each support vector after identifying the hyperplanes that offer the highest separation specified by a Kernel function. This results in a weighted sum as the algorithm's output [9].

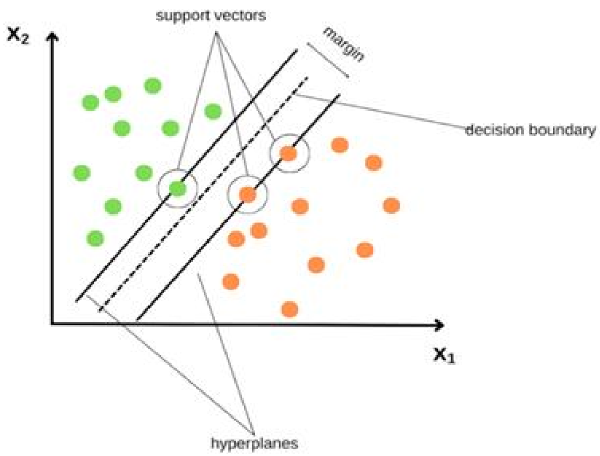

Figure. 3. SVM schematic diagram

RSSI distance-based algorithms. RSSI distance-based algorithms are those that rely on distances between RSSI vectors, also known as fingerprints. Metric distance functions like the Euclidean distance can be used to find the distances explicitly, while a Kernel function can be employed to compute the distances implicitly. Aside from the group FCHW as mentioned in the precious part, RSSI distance-based algorithms also contain the subcategory named Database Correlation Method (DCM). Weighted k-Nearest Neighbours (Wk-NN) is considered as the most commonly used implementation algorithm within the DCM group [9].

Wk-NN generates a weighted average of the k closest database components. The normalised inverse of the metric distance is used to calculate the weight function.

The approaches were tested respectively on four datasets. UJI BLE, UEx Phy, UP and UNEX-URI.The result shows that for all four datasets, Wk-NN delivered the result with highest accuracy with the average normalized error of 0.68 compared to NN. However, it requires longer time when processing. SVM performs best in this aspect, it generates the output in about 4ms [9].

2.2 Unsupervised machine learning techniques

The most obvious difference between supervised and unsupervised machine learning techniques is whether the data are labelled or not. Data used in unsupervised machine learning techniques are not labelled. This feature enhance the efficiency of data collecting process. Clustering based techniques such as Density based spatial clustering of applications with noise (DBSCAN) as well as K-means clustering are widely used in indoor localisation [10].

Density-based spatial clustering of applications with noise (DBSCAN). As can be seen from Figure 4, DBSCAN classifies the data points into three categories: core points, boundary points, and noise points, using two parameters epsilon (Eps) and minimum points (MinPts). The idea it to find a circle with radius (Eps) centred at a random point p from the data points, if the circle contains at least MinPts points, then the data point is then considered as a core point. A boundary point is any point that is included in the circle, else called a noise point. In this way, points can be clustered based on their densities [10].

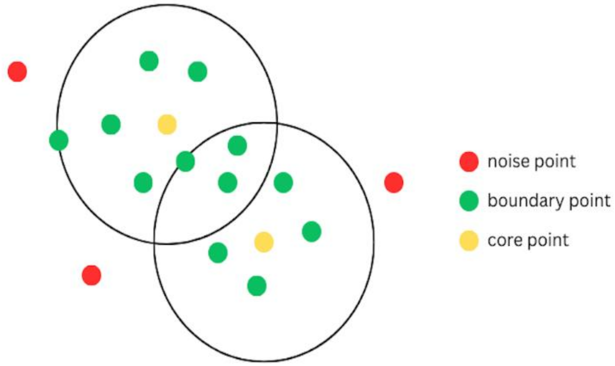

Figure. 4. DBSCAN schematic diagram

K-means clustering. In K-means clustering techniques, k clusters are first developed from random k data points, which are either the centroid or the mean value of the clusters within the given dataset, shown in Figure 5. For the rest unclassified data points, the distances from each to the nearby clusters are computed, they will then be categorised to the nearest cluster. However, the performance of this method can not be promised under the condition where the data points are moving, which produces challenge when employed in indoor localisation [10].

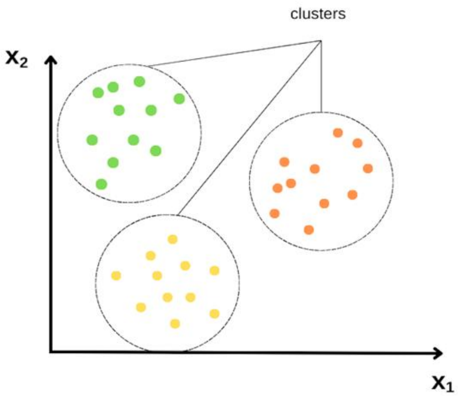

Figure. 5. K-means clustering schematic diagram

2.3 Deep learning and vector embedding

The Vector Embeddings technology is commonly referred to as the compact representation of data and is commonly used when processing speech signals. [11] first proposed an innovative approach which applies vector embedding in indoor positioning.

D-vector. As a common example in vector embedding, the d-vectors are extracted values of activation from the dense layer of the MLP model, which is a Deep Neural Network (DNN) model, as Figure 6 shows. Theoretically, any layer can be chosen to generate d-vectors. However, it is tested that in order to conduct better generalisation, the higher dense layers are often used to generate d-vectors. The data needs to be labelled when applying the d-vector. The systems with d-vectors extracted from MLP layers tend to perform similarly to the base model, which indicates that, applying d-vectors can save the complexity of DNN models as well as reduce storage space and processing costs without concerning about negative impact [11].

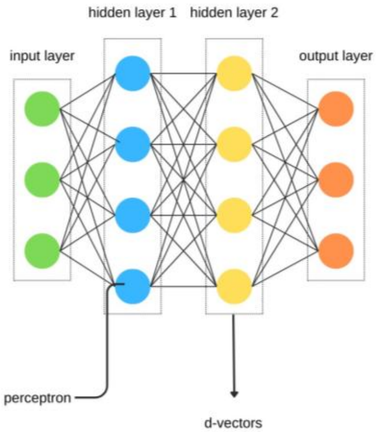

Figure. 6. D-vector schematic diagram

I-vector. An i-vector is another widely used example of vector embedding. Unlike d-vectors, which are used in location general positioning, instead, it's used in location-specific positioning scenarios. It is a characteristic vector created from universal background models (UMB). Figure 7 illustrates how DNN models can be upgraded to become location-specific by feeding them i-vectors. The model can then be used to monitor the movement of the object. It plays a crucial role when monitoring the location dynamically.

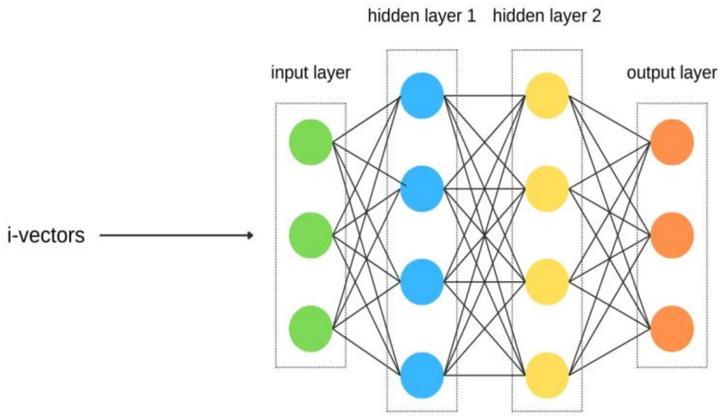

Figure. 7. I-vector schematic diagram

When comparing with a basic DNN model, which is an MLP in this case, d-vector generates similar output accuracy within a shorter time period, which indicates, the use of d-vectors will reduce the redundancy in processing data while keeping the basic performance of the original model. I-vectors can be fed into the DNN model to apply model adaptation, which can be seen from Table 1, acting as an accuracy booster which highly increases positioning accuracy from 75.47% to 80.62%.

Table 1. Result comparison of vector embedding examples

Method	Training Time	Classification Delay	Accuracy
Standard DNN	40.3s	0.1s	62.86
d-vector	low	0.1s	61.68
i-vector with model adaptation	<40.3s	fast	80.62
DNN without model adaptation	40.3s	0.1s	75.47

3 Comparison

All the algorithms are tested based on WiFi or BLE fingerprinting, which a is widely used indoor positioning technology. Combining the analysis from previous part, in summary, vector embedding is an advanced technology and with i-vectors, it can be applied in scenarios where movement detection is needed. Supervised machine learning techniques are conventional indoor positioning systems, however can still be optimized such as finding the most effective k value for Wk-NN and the number of perceptron layers for MLP. It has been tested that Wk-NN is the most accurate, but it takes longer time, so it’s suitable when there are less beacons providing less data to process. When there are a great deal of data points, SVM seems to be the most effective owing to its rapid processing process. When it comes to noises, DBSCAN, which is an unsupervised machine learning technique, is the most effective option since it classifies the data points based on the density.

4 Future work and challenge

Indoor positioning systems is a foundation for indoor navigation systems and navigation requires real time reaction. Thus, how to conduct highly-accurate positioning while reacting to the changes instantly is definitely an on-going issue to be solved. Moreover, in complex indoor environments like shopping malls and airports, there will be multiple users, the indoor positioning systems will be optimised so that it can tackle multiple signals without disturbing and interference.

Future work will be focused on the combination of these methods to be adapted to dynamic positioning as well as reducing signal disturbing. Additionally, since indoor positioning systems will play a crucial role in emergency situations like rescuing after an earthquake, combining it with human sensing also worth investigating. Last but not least, future research should also investigate on how to protect users' privacy when high accuracy position data are being employed [12].

5 Conclusion

This work conducts a comparative analysis of three popular AI algorithms that can be used in WiFi or BLE fingerprinting indoor positioning systems, including supervised, unsupervised machine learning algorithms and vector embedding combined deep learning algorithms. Results show that vector embedding examples, especially with i-vectors tend to perform most accurately while unsupervised machine learning can be used to deal with noise data points to deliver more precise results. However, supervised machine learning techniques are still considered as the most efficient with respect to both the computation cost and performance accuracy.

This comparative work will provide a useful perspective on some existing implementation methods as well as their strengths and weakness to be applied in different scenarios, which can be used in future urban planning.

Looking ahead, indoor positioning systems will definitely play a crucial role in complex indoor environments such as airports, shopping malls and hospitals. Future work will focus on to provide high accurate real-time response of these systems, also to investigate on how to avoid signal interference when there exists multiple users. By combining with human sensing techniques, indoor positioning systems can also be employed in emergency rescues and elderly monitoring.

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