Indoor Localisation using Existing WiFi Infrastructure - A Case Study at a University Building

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***Abstract*—Location is an important context in everyday activity. Outdoor positioning, through the use of the Global Positioning System (GPS), has been a mature technology. Indoor localisation, on the other hand, is still an active research area. While many popular techniques utilise new specialised, dedicated devices to enable precise indoor positioning, our investigation aims to solve the indoor localisation problem by using only existing WiFi infrastructure and commercially-off-the-shelf (COTS) smartphones. Based on the algorithm from previous investigations, a case study was carried out at a typical university building. Location clusters were generated using WiFi information collected using a COTS smartphones. Fingerprints were then formed from the generated clusters. Two evaluations have been carried to perform the comparisons. This paper discusses the obtained results, observations and issues faced in the case study.**

***Index Terms*—Indoor Localisation, WiFI, RSSI, DCCLA, Density-based Clustering, Smartphone**

I. Introduction

Location has always been an important factor in our everyday lives. Outdoor Global Positioning System (GPS) is a mature technology. It is widely used in different areas to provide outdoor location information for location-based services (LBS). However, GPS technology does not work well in the indoor environment. This is mainly due to fading signals caused by obstacles such as ceilings, roofs and walls of buildings. Therefore, there is a need for alternative methods to implement indoor localisation.

Indoor positioning is an active area of research in the past decades. It aims to provide accurate indoor positions of a person or a device . Some of these techniques make use of radio technology that serves as hooks or sensors for indoor positioning. Among these technologies are like Apple's iBeacon [1] [2], Radio-frequency identification (RFID), Ultrasonic and Wireless Fidelity (WiFi) access points [3] [4] [5] [6]. Besides the use of wireless transmission technologies , other types of sensors such as the gyroscope , accelerometer and compass found in wearable devices or smartphones as well as laser [4] technology are also applied in recent indoor localisation investigations.

Many of the above solutions require new installations of dedicated sensors to achieve reasonable to good indoor localisation. This will incur additional costs and resources, not only for new installation but also for maintenance as well as sensor calibration. It will be particularly costly when such solutions should be implemented in existing buildings [9]. For example, iBeacon or technology based on Bluetooth Low Energy [7] will have limited range and may require extensive calibration if high accuracy on the variety of spaces is required. An RFID-based solution will require sufficient base stations to be installed in designated areas and dedicated RFID tags needed to be worn. Cold start problem is also unavoidable - Many solutions will depend on a longer preparation and learning phase before the systems can be ready to be deployed.

The alternative to the above techniques will be the solutions that leverage on any existing infrastructure. Such solutions will incur lower costs since no new installation of hardware is required . For example , WiFi infrastructure is very common nowadays for many existing buildings. If a feasible solution can be built based on WIFi technology , it will be seen as a cost-effective solution as compared to those mentioned above . Another category of indoor localisation is known as the infrastructure-less or infrastructure-free indoor positioning . It acquires location information using projected patterns obtained from sensors like microphone , magnetometer and even light sensor of a smartphone [8], [9].

In this paper, an infrastructure-based WiFi-only localisation technique is presented. The motivation behind this approach is the observation where WiFi access points are almost ubiquitous in urban public spaces . Apart from its relatively high availability , the low adaptability cost is also a factor why we consider WiFi as an attractive method. These factors can further cut down cost in manpower and time in the implemen- tation of indoor localisation [3]. Also, the desired localisation will be room-level localisation . The concept of meaningful location will be the expected outcome of the proposed indoor localisation solution. In other words, the envisioned system will attempt to recognise locations with lower granularity , such as rooms or sections of a corridor.

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This paper is organised as follow: Section II presents related work to indoor localisation. Section III presents the algorithms briefly and methodology that has been executed. This section includes the details of the algorithm, together with the pseudo code and explanation. In Section IV, the evaluation and its results on accuracy of the system will be shown and explained. Finally, the conclusion will be in the last section of this paper.

II. Related Work

Indoor positioning has been one of the most actively researched areas in recent years. Related work to this case study will be focused on approaches that made used of a different method for localisation, and then to the ones related to this case study.

Apple iBeacon [7] is one of the examples of indoor positioning, where it uses Bluetooth beacons to ping for the location of a user from a particular beacon to estimate the area of the user. A company named Wifarer [10] is aware of the outdoor-only GPS system, and has come up with a system that uses WiFi Access Points and Bluetooth Low Energy beacons to generate digital fingerprints to position the users indoor. However, both methods use the Bluetooth LE beacon and WiFi Access Points for positioning. Such approaches will require the users to invest in new infrastructures. Our proposed method intends to use only WiFi Access Points.

Infsoft [11] is also a company that runs the business on indoor navigation. This company makes use of the sensors, such as the compass, gyroscope, barometer, accelerometer, air pressure and magnetic fields, with the help of WiFi, GPS (for outdoor), Bluetooth and 3G/4G connection. However, this technique requires additional infrastructure, where intensive site survey of locating the additional Bluetooth sensors has to be done for the whole system to run, which will take a long time and it is also costly regarding manpower and time, not to forget the size of the building.

One of the techniques which use no extra sensors and hardware as hooks is Unloc [12], where it uses the mobile devices' sensors and WiFi access points to locate the mobile phone indoors, without requiring prior explicit labelling or work to be done for site surveying. In this paper, we will be using Density-based Clustering Combined Localisation Algorithm (DCCLA) [13], an unsupervised fingerprint building technique which had been tested in both laboratory [13] and an open area - Sunway Pyramid Shopping Mall [14]. This DDCLA approach will eliminate the need for site-survey or pre-deployment process found in supervised fingerprint building technique. DCCLA works by collecting WiFi Access Point RSSIs in the background of a user'??s smartphone. When a person stays at a location for a longer time than usual, the system then detects if the WiFi Access Point'??s RSSIs are similar, which would result in a high-density distribution, then creates WiFi fingerprint based on the information collected. The advantage of DCCLA is that it is more cost effective as no pre-deployment process or site survey is needed, and they have used clustering in their WiFi fingerprint, which is a range of RSSIs of a location or place, which they found is more informative instead of a list of representative or calibrated RSSIs. However, battery consumption of DCCLA on a smartphone is a concern as the WiFi receiver will have to scan the WiFi Access Points all the time whether or not it is still needed.

Another example of is Zee: Zero-Effort Crowdsourcing for Indoor localisation [15]. It utilises Radio Frequency (RF) fingerprints, based on WiFi Access Points and Cellular Networks to locate a person indoors with the help of a mobile device's inertial sensors such as the gyroscope, compasses and accelerometers.

In [16], they have pointed out that selection of Access Points is an important criterion for improving the accuracy of indoor location estimation. The selection of the best Access Points can affect the results severely. As a conventional WiFi-based indoor positioning systems, they have made used of KNN (K- Nearest Neighbour) concept which they pointed out, is should be on the top of the list of choices for indoor positioning and localisation with little or none prior data of the distribution of the data in a specific location. Therefore, they introduced Novel Access Point Selection Strategy. In this strategy, they will first collect and analyse location with different numbers of Access Points. Moreover, then, they will pick the best Access Points and only keep the good ones. As such, it will not burden the system as the system has a shorter list of locations to go through during positioning. While in this research, we will look into possible ways to optimise the selection of the Access Points as our available everywhere in the University. As such, we will be doing tests on the best ways to collect training data which will reflect the best results in recognition.

III. WiFi Fingerprint localisation Density-based Clustering

The investigation in this paper is carried out based on the algorithm from the authors' previous work. This algorithm, the Density-based Clustering Combined Localisation Algorithm (DCCLA) [13] [17], is responsible to generate the fingerprints needed for location recognition. A pseudocode of DCCLA is shown in Algorithm 1.

The DCCLA technique was originally proposed to build WiFi fingerprints with none to a minimal amount of on-site site-survey [13] [17]. However, the experiments were carried out in an office environment with no occupants. The results of the investigation have shown the algorithm's potential and obtained a usable localisation accuracy. Then, the algorithm was being tested in a real-world environment, to test the potential of the algorithm's capability to recognise locations in a shopping mall [14]. The results showed accuracy between 33% up to 88%. In this paper, the research is extended to a university building environment to see its performance as compared to previous work. We expect the results to be better for a university building than the shopping mall, mainly because it has more structural and wall designs. In a shopping mall, the locations with lower accuracy are usually the open areas.

Algorithm 1 Density-based Clustering Combined Localisation Algorithm (DCCLA)

procedure DCCLA
  Separate the collected RSSI points into datasets, each dataset with a unique MAC address MAC_i.
  Order each dataset to form a list L_i, with increasing RSSI values.
  Label each RSSI points (P_{ik}) on each list L_i as unchecked
  for each ordered L_i **do**
    while there exist an unchecked P_{ik} **do**
      Calculate the *Neighbourhood density* of P_{ik} (p(P_{ik}))
      if (p(P_{ik}) is smaller than *MinPts* **then**
        Label P_{ik} as checked
        continue the while loop
      else if P_{ik} belongs to an existing cluster C_i^o **then**
        Merge neighbourhood of P_{ik} to C_i^o
      else
        Create a new cluster C_i^p
      Label P_{ik} as checked

A. The algorithm

There are two different phases in the DCCLA technique. The first phase is the learning phase. The DCCLA will build fingerprints from the collected data based on the received signal strength indicator (RSSI) patterns of the WiFi access points found near a particular location. A fingerprint is generated from clusters formed based on the density of the RSSI signals collected over a certain period of time. A fingerprint database is the created from all the generated fingerprints. This fingerprint database will be used as a model for the recognition phase to enable indoor localisation through location recognition, which is the second phase.

The recognition algorithm involved in the second phase is straightforward and clear. A matching algorithm will check the number of successful matches between a scan instance of the WiFi receiver and the fingerprints in the database . The best-matched fingerprint will be the winner , and the recognition algorithm can then predict a location . In our recent work , a successful recognition will happen when the number of matches exceeded a pre-defined threshold percentage of matches [14]. This algorithm will also be the default recogni - tion algorithm used in this paper.

B. Data Collection

This case study has been carried out at the Sunway University. As Sunway University has an almost complete WiFi Coverage in its vicinity, which allows us to fully utilise such WiFi access point coverage for indoor positioning. This paper intends to test the performance of indoor positioning based on existing WiFi infrastructures in Sunway University. We would also like to study the differences and effects of localisation accuracy for two settings. The smartphone may be placed at a stationary position for data collection, or it may be held by a person for the same purpose. We expect the accuracy of the stationary setting to be higher than the handheld setting.

Once WiFi signal information has been collected for selected locations, WiFi fingerprints are built using DCCLA algorithm. The investigation carried out in this case study are performed at Sunway University during normal hours where students have finished their classes or going to their respective classes, having classes, and even after class hours. The data was collected using Commercial-Off-The-Shelf smartphones. Data was collected using the smartphones by having a student helper to collect open and available WiFi data detected at the selected locations. In order words, the smartphone performs a WiFi scan for available access points around the vicinity and all captured WiFI RSSI from detectable access points will be stored. No modification or tweaking was done on the used smartphones and their respective operating systems.

During each collection , while the phone is collecting data and the helper does not need to stand stationary , he/she can sit and leave the phone on a platform (a chair or a table) within their sight to prevent the phone from being misused or carried away.

One interesting observation we had is the detection of a fair number of portable APs. These are usually the mobile hotspots carried by users , allowing them to tether their mobile devices with wireless 4G Internet . This observation showed a common phenomenon in public and open spaces, such as a university , as some students prefer to use their internet connection . For the proposed indoor localisation system , these APs were not considered . They will be filtered and removed from both fingerprint training and detection.

IV. Evaluation Results and Discussions

Three sets of WiFi data have been collected for this paper. The datasets cover 6 locations at the level 3, West Wing of the New University Building (NUB) of Sunway University. These locations are Postgraduate Lab 2, Postgraduate Lab 1, SUBS Postgraduate Lab, Entrance, Lift Lobby and Classroom UC3-3. Figure 1 depicts the floor plan of the locations selected for the evaluations in this paper.

The first set of data is used as the training data. Each location consists of 40 minutes of data. This gives a total of 240 minutes of data, which translate to a total of 7136 WiFi

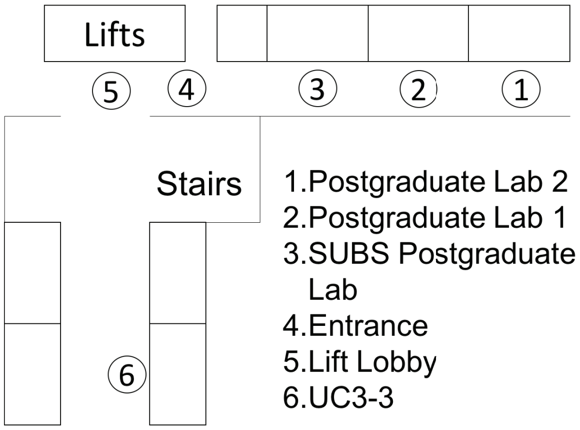

Fig. 1. Floor plan of the locations selected for this paper

signal instances. A fingerprint database is generated using the DCCLA algorithm. The second and third sets of data are the test data. The second set of data consists of 20-22 minutes for each location. The total duration of this set of data is 126 minutes (3809 instances). The second set of data was collected with the smartphone being placed stationary on a chair at the locations. The final set of data is collected by a subject holding the smartphone and standing at the locations. The total duration of this set of data is 16 minutes (291 instances), where each location has 2-3 minutes of data.

For the evaluations, the second and third sets of data will be tested against the fingerprint database generated from the first set of data. The first evaluation intends to evaluate the localisation accuracy of the fingerprint database with data collected in a stationary condition. The second evaluation will evaluate the localisation accuracy with the data collected in a handheld condition. Both results are presented in the next subsection.

A. Evaluation results

The evaluation results are shown in the following tables Table I and Table II. The first evaluation (see Table I) has shown an accuracy ranging from 97.28 % to 99.85 %. Since the smartphone was placed on a chair and remained stationary all the time, such high accuracy is expected. Nevertheless, the RSSI values are not static throughout the collection for all locations. It is observed that there is a variation of 3 dBm from the second set of data.

For the second evaluation (see results in Table II), the accuracy obtained ranged from 81.82 % to 92.31 %. As compared to the results shown in Table I, it is relatively lower, especially for the location Lift Lobby. Due to mainly the size of the third set of data, the obtained accuracy is identical for all locations except Lift Lobby. From the floor plan (see Figure 1), the location of Lift Lobby is situated at a more open area, and it is also next to the stairs. From our past investigation [14], it was observed that open areas would usually be more difficult to achieve higher localisation accuracy.

TABLE I
EVALUATION 1: ACCURACY OF THE FINGERPRINT DATABASE TESTED WITH DATA COLLECTED IN A STATIONARY CONDITION

Location	Time (mins)	No. Instances	Accuracy (%)
Postgraduate Lab 2	22	637	99.70
Postgraduate Lab 1	20	602	99.67
SUBS Postgraduate Lab	21	647	99.85
Entrance	20	624	97.28
Lift Lobby	21	634	99.37
Classroom UC3-3	22	665	99.70

TABLE II
EVALUATION 2: ACCURACY OF THE FINGERPRINT DATABASE TESTED WITH DATA COLLECTED IN A HANDHELD CONDITION

Location	Time (mins)	No. Instances	Accuracy (%)
Postgraduate Lab 2	3	52	92.31
Postgraduate Lab 1	3	52	92.31
SUBS Postgraduate Lab	3	52	92.31
Entrance	2	39	92.31
Lift Lobby	2	44	81.82
Classroom UC3-3	3	52	92.31

During the evaluation, it is found that many locations have WiFi access points that are unique to a particular location with a fixed RSSI range known as significant APs. This information can be used to further improve the recognition accuracy as it is an identifying factor of the particular location.

B. Discussions

From the results obtained above, it is observed that the accuracy for the stationary collection is higher than the handheld ones. The duration may play a role. Another observation is the variation of RSSI values for the collected data. The data from the handheld condition has a larger RSSI value variation range. The range is between 4-5 dBm. Compared to the 3 dBm, observed in the stationary data set, the slightly larger RSSI value variation may be another factor of the lower accuracy. Therefore, the higher number of occurrences of the same access points with different ranges can contribute to the differences in the results of the localisation accuracy. Nevertheless, the DCCLA can build fingerprint database that allows RSSI signal variations between 3-5 dBm. This will be helpful in providing more accurate location detection for an indoor environment.

C. Future Work

From the outcome above, for a higher localisation accuracy, the inclusion of smartphone sensors may be applied. If movement and direction change can be detected, the localisation system may use these contexts to help improve the localisation technique. By remembering a recognised location, new detection will only be made if the subject has moved from the original location. With improved accuracy, location information for an indoor environment can be integration in existing and new applications designed to serve the university community.

V. Conclusions

In this paper, we have presented results of two sets of data, stationary and handheld, of different duration during WiFi access point information collection. Longer collection time has produced highest accuracy. Nevertheless, the second set of data has provided promising results. It is found that DCCLA approach does work well in a real-world environment such as a university like the Sunway University, which is well equipped with wireless access points. Such infrastructure be useful to enable indoor localisation.

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